Development of a software application utilising classical efficiency theory, regression and Data Envelopment Analysis in the evaluation of thermal power plant performance.

by Almero de Villiers

Thesis presented in partial fulfilment of the requirements for the degree of Master of Science in Engineering at the Stellenbosch University

Supervisor: Prof. H.J. Vermeulen
Department of Electrical and Electronics Engineering
December 2015

Declaration

By submitting this thesis electronically, I declare that the entirety of the work contained therein is my own, original work, that I am the authorship owner thereof (unless to the extent explicitly otherwise stated) and that I have not previously in its entirety or in part submitted it for obtaining any qualification.

Date: ………………………………….

Abstract

Recent capacity constraints on the South African power grid, coupled with the economic and environmental implications of increasing energy requirement, has given rise to major efforts to implement energy management initiatives in the industrial, commercial and residential load sectors. These efforts are supported by the construction of multiple new power plants, both thermal and renewable in nature. Additionally, the Energy Efficiency (EE) of existing plants is being optimised, which requires accurate performance evaluation and benchmarking as part of plant diagnostic and Measurement and Verification (M&V) exercises.

Energy management exercises require accurate tracking of power plant efficiency. In this project a South African coal-fired power plant is used as a test case, and is analysed utilising both classical and Data Envelopment Analysis (DEA) based EE evaluation methods in an attempt to track plant efficiency over time and in relation to similar US plants. DEA is a non-parametric linear programming-based benchmarking technique used to comparatively evaluate multiple peer branches. The historical plant data used in this project is provided in monthly intervals, but is of low quality, with measured fuel consumption values out of sync with actual fuel consumption values. For this reason data averaging is also considered. A software application is developed to analyse historical plant data, supported by the development of a relational database. This database allows for permanent storage and access of historical plant data while the software application incorporates all relevant analysis methodologies and graphic user interface.

The classical efficiency evaluation methods are found to provide a general overview of actual plant performance, but do not consider plant context, often making results ambiguous. The methods are also limited to energy datasets, and cannot incorporate additional factors that may be relevant to plant performance. Higher quality data is recommended to increase the accuracy of results.

M&V interventions include an energy audit before and after an EE implementation. Pre-implementation data is referred to as the baseline and is used to evaluate the positive impact of the implementation. Regression analysis is investigated as a means of gaining additional insight into the effect of additional factors on overall plant efficiency, but also as a means of baseline adjustment in an M&V context. The regression analysis study does not produce significant results, but increasing the quality of measured plant datasets may allow for more useful results.

The DEA efficiency tracking methodology is found to be of use when additional factors are incorporated with energy data, and can provide a brief overview of performance between plants. When a single plant is evaluated over time the process can also easily identify inefficient periods,

although additional insight is required to establish the sources of these inefficiencies. DEA is thus not a complete replacement for classical EE methods, but rather a useful supplementary tool in efficiency evaluation. The accuracy of its results is highly susceptible to the quality of data used. Evaluation of individual plant component inputs and outputs rather than overall plant inputs and outputs would make for a useful future study.

Opsomming

Onlangse kapasiteitstekortkominge op die Suid-Afrikaanse kragnetwerk sowel as ekonomiese en omgewingsimplikasies van toenemende energiebehoeftes het aanleiding gegee tot 'n intensifisering van die pogings om energie bestuursinisiatiewe in die industriële, kommersiële en residensiële ladingsektore te implementeer. Hierdie pogings word vergestald deur onder andere die skepping van nuwe en alternatiewe opwekkingsfasiliteite. Verder word die bestaande sentrales se Energie-Doeltreffendheid (ED) geoptimaliseer, wat die verbetering van akkurate prestasie-evaluering en maatstawwe as onontbeerlike element van die sentrale se diagnostiese en Meting en Verifikasie (M&V) oefeninge vereis.

Energie bestuuroefeninge vereis die akkurate begeleiding van kragsentrale doeltreffendheid. In hierdie projek word ‘n Suid-Afrikaanse steenkool-aangedrewe kragsentrale gebruik as ‘n toets onderwerp, en die analise van beide die klassieke en Data Omhulsel Ontleding (DOO) gebaseerde ED evalueringsmetodes in ‘n poging om die kragsentrale se doeltreffendheid na te spoor oor ‘n gegewe tydperk in verhouding met soortgelyke Amerikaanse kragsentrales. DOO is 'n nie-parametriese lineêre programmering-gebaseerde maatstaf tegniek wat gebruik word om vergelyking te tref met verskeie ander soortgelyke takke. Die historiese kragsentrale data wat in hierdie projek gebruik word, is verskaf in maandelikse frekwensie. Die kwaliteit van die data word bevraagteken. Dit bevat gemete brandstofverbruik waardes wat uit verhouding is met die werklike verbruikswaardes. Om hierdie rede word die data wat verkry is vergemiddeld. ‘n Sagteware program is ontwikkel om historiese kragsentrale data te analiseer en word ondervang deur die ontwikkeling van ‘n verwante databasis. Hierdie databasis sorg vir permanente storing en toegang tot die historiese kragsentraledata, terwyl die sagteware program alle relevante analise metodes en ‘n grafiese gebruikerskoppelvlak insluit.

Die klassieke doeltreffendheid-evaluering metodes verskaf ‘n algemene oorsig oor die werklike prestasie van die kragsentrale, maar neem nie die kragsentrale se unieke omstandighede in ag nie wat veroorsaak dat die resultate dubbelsinnig van aard kan wees. Die metodes word beperk tot energie datastelle en kan nie bykomende faktore wat relevant is tot die kragsentrale prestasie assimuleer nie. Hoër data kwaliteit word aanbeveel om die akkuraatheid van die resultate te verhoog.

‘n M&V intervensie bevat ‘n energie-oudit voor en na die ED implementering. Die basislyn is voorimplementerings data en word gebruik om die positiewe impak van die implementering te evalueer. Regressie-analise is ondersoek as ‘n metode tot die verkryging van bykomende insig in die effek van bykomende faktore op algehele opwekkingseenheid doeltreffendheid en ook as 'n middel

om die basislyn aanpassing in 'n M&V konteks te bepaal. Die regressie-analise studie bied nie beduidende resultate nie. Die verhoging van die kwaliteit van die gemete kragsentrale datastelle mag moontlik bruikbare resultate verskaf.

Die gebruik van die DOO doeltreffendheid metode is effektief wanneer daar bykomende faktore by gewerk word tot die energie data en kan as n kort vergelykende oorsig van die prestasie tussen die verskillende kragsentrales gebruik word. Wanneer ‘n enkele kragsentrale oor n tydperk evalueer word kan die proses ook maklik ondoeltreffende periodes identifiseer. Bykomende insig is nodig om die bronne van hierdie ondoeltreffendheid te bevestig. DOO is dus nie 'n volledige vervanging vir klassieke energie-doeltreffendheid metodes nie maar eerder 'n nuttige aanvullende hulpmiddel van doeltreffendheid evaluering en verifikasie. Die akkuraatheid van die resultate is baie vatbaar vir die gehalte van die data wat gebruik word. Evaluering van individuele kragsentrale komponent insette en uitsette eerder as algehele kragsentrale insette en uitsette sou as grondslag van n toekomstige studie-onderwerp kan dien.

Acknowledgments

I would like to thank Prof HJ Vermeulen for his valuable guidance and efforts throughout this project, without which this study would not have been possible. Furthermore I would like to thank my mother, father, sister and Anelle for the massive amount of support they provided during the past few months.

Contents

List of figures

List of tables

List of abbreviations

DB	Database
DBMS	Database management system
DEA	Data envelopment analysis
DLL	Dynamic link library
DMU	Decision making unit
DSM	Demand side management
EE	Energy efficiency
EEDSM	Energy efficiency and demand side management
EM	Energy management
ESCo	Energy service company
FK	Foreign key
GJ	Gigajoule
GUI	Graphic user interface
IDE	Integrated development environment
J	Joule
kg	Kilogram
KW	Kilowatt
KWh	Kilowatt hour
LP	Linear programming
M&V	Measurement and verification
MAE	Mean absolute error
MJ	Megajoule
MW	Megawatt
MWh	Megawatt hour
PK	Primary key
QL	Query language
RMSE	Root mean square error
RTS	Return to scale

SQL	Structured query language
UML	Unified modelling language
UP	Unified process
VCL	Visual component library
WAMP	Windows apache MySQL PhP
XML	Extensible mark-up language

1 Overview of project

1.1 Introduction

The South African power grid has been experiencing severe capacity constraints in generation and transmission in recent years, with a dramatic decrease in the size of the allocated reserve margin [1]. This, coupled with the decrease in the availability of fossil fuels, and the economic and environmental implications of the globally increasing energy requirement [2] has given rise to major efforts to implement Energy Management (EM) initiatives in all load sectors, including the industrial, commercial and residential sectors [3]. These efforts are supported by the construction of multiple new power plants, both thermal and renewable in nature. Additionally, the Energy Efficiency (EE) of existing plants is being optimised, which requires accurate performance evaluation and benchmarking as part of Measurement and Verification (M&V) exercises. There are several advantages to increased plant EE. These include both increased unit generation and reduced operating costs as well as reduced costs to the consumer. Also it is hoped that finite fuel will last longer and that the emission of the greenhouse gas CO_2 and other pollutants will be reduced [4].

M&V exercises are used to determine the energy savings of an EE project, while providing unbiased feedback to all project stakeholders. This is done by measuring energy usage and demand before and after the completion of the intervention [5]. M&V baselines are usually constructed using historical data and adjusted where necessary to produce more accurate results. M&V activities are utilised by Eskom to assess and monitor the performance of EE projects [6] and, internationally, are required in certain federal EE contracts [5]. To be of use, it is imperative that power plant M&V activities need to accurately track plant inputs and outputs, as well as overall plant efficiency [6]. This efficiency may need to be calculated using incomplete or low-fidelity datasets. Once the dataset is acquired, M&V personnel can potentially formulate plant baselines using additional plant information to implement accurate adjustments in performance.

Besides EE and M&V efforts, plant efficiency can be increased by the optimisation of existing internal practices and processes. This requires the continual and accurate tracking of plant efficiency, making it possible to identify the presence and nature of inefficiencies to be identified. The results of efficiency tracking can be used by plant management personnel to address these issues. Under-performance detection also allows management to easily monitor plant economics.

1.2 Project motivation

Currently almost 99% of South African electrical energy is generated by thermal plants [7], with a further 9600MW capacity increase under construction at the time of writing [8]. As such, EE projects focusing on thermal power plant efficiency have the potential to make significant positive impacts on national energy usage. South Africa has received funding from the world bank to build additional power plants, as well as to increase the efficiency of our existing plants. M&V serves as validation of these improvements [6]. If a plant is benchmarked over time, its inefficient periods are highlighted [9], which allow the sources of these inefficiencies to be identified and addressed. In addition, more efficient periods can be emulated in some way [10]. When evaluating the efficiency of a power plant, a useful exercise is benchmarking against other plants, so as to gain insight into the plant's comparative performance. The selection of these plants is important, as plant vintage, technology, fuel quality and geographical location can have significant impacts [11].

Thermal plants are often criticised for their negative impact on the environment. Power plants are responsible for almost 25% of all greenhouse gas emissions and are thus major contributors to global warming and climate change [2]. Coal, as the largest provider of energy, is also responsible for numerous other pollutant emissions such as sulphur dioxide (SO_2), nitric oxide and nitrogen dioxide (collectively as NO_x) and particulate pollution [12], as well as ash and soot [11]. Coal fired plants typically release 26,4kg of Carbon per GJ sent out [13]. Thus, alongside EE efforts, the "eco-efficiency" of thermal power plants is also being minimised, with multiple projects aiming to reduce plant emissions while increasing output [2] [3].

Traditional methods of evaluating power plant EE performance, such as heat-rate monitoring [13], are difficult and often produce inconclusive results due to a lack of online data and the complex nature of factors, such as environmental conditions, that determine the overall efficiency of the plants. Furthermore, the different national standards used for heat rate monitoring can produce results for the same plant that vary by as much as 2% [4]. The savings impacts of many individual EE interventions are small compared to the plant ratings, resulting in difficulties in extracting the savings impacts from noisy baselines. These methods may also be too rigid in structure to allow for use in both comparative benchmarking between individual plants and a time-based evaluation of a single plant e.g. month-to-month or year-to-year. Ambiguity can easily arise when determining the efficiency of a plant, as various plant components (such as the boiler, turbines etc) are often evaluated independently, rather than in the context of the entire facility [4].

Baseline adjustments are a crucial step in M&V, serving to account for external factors that may have a significant effect on project performance [5]. Baseline adjustment can also be used to account for changes in metering equipment or overall project scope at later stages [6]. The methodologies used in adjustments need to be flexible so as to be used in any desirable project. However, there is, to date, no formal method dedicated to baseline adjustment when performing M&V in a power generation context.

Data Envelopment Analysis (DEA) is a data-oriented, non-parametric benchmarking technique that utilises linear programming as its basis. DEA comparatively evaluates numerous peer branches, or Decision Making Units (DMUs), making use of multiple numeric input and output categories [10], which can consist of any quantifiable values, thus allowing any factor deemed relevant to be incorporated in the analysis [14].

DEA has been used in the past to comparatively evaluate plants (both thermal and renewable) and serve as a plant benchmarking tool [15, 16]. The process has also been used in other power generation-related roles, such as an environmental impact assessment tool [17] and in renewable energy contexts [18]. Regression analysis has also been combined with DEA [19]. The efficiency metric tracking capabilities of DEA may allow it to serve as a valuable diagnostic tool for power plant managers. DEA may also present a novel means to gain insight into the EE performance of power plants by tracking a metric of performance efficiency over a given timeline, serving as a valuable benchmarking tool for M&V applications. When applied to plant datasets, it may help identify the periods in which the plant did not perform as well as desired. DEA may also serve to identify the nature of any plant inefficiencies and can serve to provide insight into the economic performance of the plant.

1.3 Project description

1.3.1 Overview of project description

The aim in this project is to evaluate the overall efficiency of a target South African coal fire power plant by utilising classical efficiency evaluation methods. The plant is benchmarked against a US plant of similar design and vintage, as well as a modern US coal fired plant. This is done to establish the relative performance of the South African plant. The efficiencies of all three plants are tracked over time, to identify any similarities in seasonal trending. Energy efficiency efforts are imposed on the target plant during the first year of data. Thus, the efficiency results are analysed to establish the extent of these energy savings. Results are used in regression analyses to gain additional insight into the factors that may affect plant performance. In addition to classical efficiency evaluation methods, DEA efficiency tracking is employed to incorporate external factors in the analysis, potentially highlighting new plant information. DEA's ability to provide additional insight into plant performance is examined. Both classical and DEA efficiency evaluation methods must comply with the following:

- Must make use of historical plant data.
- Must utilise classical efficiency evaluation techniques and DEA theory, models and orientations to evaluate plant efficiency.
- Must include an implemented database-centred software application.

The implementation of both the classical and DEA efficiency evaluation methodologies includes the development of a software application. This is an integral part of the project, as evaluating historical plant data can be complicated and an automated process will aid in this study. This application makes use of classical efficiency methods as well as various DEA models and orientations to analyse power plant datasets. The specific software application is thus considered a project outcome. Furthermore, regression analysis is investigated as a means of providing further insight into the effect of additional parameters, such as climate and operation datasets, on plant performance, as well as a method of baseline adjustment in the context of M&V.

During this project it is attempted to track the efficiency of the target plant via time-based efficiency tracking, as well as in comparison to other plants. An outcome of the project is thus accurate efficiency records for the target plant. Regression analysis is preformed using these results and additional plant datasets. In this project it is attempted to track the efficiency of plants over time using DEA. Various categories of inputs and outputs are considered to produce results. These results are compared to classical efficiency analysis data and their accuracy evaluated. Thus, another expected output of the project is accurate DEA-derived efficiency records.

1.3.2 Research objectives

In view of the considerations in section 1.3.1, this project aims to investigate the performance of the target South African plant both over time and in comparison to similar US plants. This is done by making use of both classical and DEA-based efficiency evaluation theory. The primary research objectives are listed below:

- To perform a literature study to research relevant topics, including coal fired power generation, measurement and verification, relational databases, integrated development environments, software design, statistical methods for data validation, and previous research into DEA's use in power generation contexts.
- To evaluate the efficiency of a South African target plant over time, as well as in comparison to similar US plants, using classical efficiency evaluation methods. Inefficiencies are identified and investigated. Seasonal variations in target plant performance are identified and compared to those of US plants.

- To determine the extent to which regression analysis can provide additional insight into plant performance.
- To determine the usefulness of DEA as a tool to track the energy efficiency performance of the target plant, as well as a comparison method with other plants. DEA's ability to identify not only the presence but also the source of plant inefficiencies is investigated. Furthermore, DEA's ability to incorporate additional plant data, such as climatic, environmental impact, fuel mass and calorific value, and capacity factor datasets, should be investigated as a means of gaining additional insights into plant performance.
- To determine the required quality of data necessary to perform accurate classical efficiency analyses and DEA efficiency analyses on plants. The data accuracy, sampling rate and range of inputs and outputs should be considered, as well as the effect of averaging over multiple performance cycles, such as seasons or years.
- To implement classical efficiency and DEA theory-based algorithms as part of a user friendly software application with back-end database support. This is supported by the development of a relational database structure that can be used to effectively store historical data used in this study.

This investigation must consider the following:

- Historical generation data, both with and without monthly or yearly averaging.
- Thermal power plants of various technologies and locations (in the case of this study the target plant is South African, while two additional US plants are also considered).
- The utilisation of various regression (curve-fitting) models.
- The utilisation of multiple DEA methodologies (envelopment and multiplier models, input- and output-orientated as well as various return-to-scale orientations).

1.3.3 Key questions

This project aims to answer the following key questions:

- Can an efficient relational database be developed to store historical plant data and which database platform is best suited to this application?
- Can regression analysis be used to make meaningful baseline adjustments when used as an M&V tool?
- Can DEA serve as a useful diagnostic tool for power plant managers to both identify the presence and exact nature of a problem in plant operations?

- What are the data criteria in terms of accuracy, sampling rate and choice of inputs and outputs necessary for accurate classical power plant efficiency and DEA efficiency tracking and can the accuracy an interpretation of classical and DEA efficiency results be improved by considering averaging over multiple performance cycle?
- Can a software application be developed that connects to the previously implemented relational database to perform the above-mentioned efficiency evaluation tasks via a user-friendly graphical user interface (GUI)? Which software development platform is best suited to the development of this application? Which existing libraries can be used for DEA linear programming problems and which are most suited to this application?

1.3.4 Research tasks

This project consists of the following primary tasks:

- *The development of a Delphi-based application and corresponding GUI:* This GUI should allow the user to select the plant or plants to be evaluated, the time-frame and the input/output categories to be included in the analysis. It should also allow the user to select the methodology to be utilised in the analysis, as well as whether a comparative or time-based analysis is performed.
- *The development and integration of an efficiency evaluation software module:* This includes actual, scale and technical efficiency, as well as heat rate.
- *The development and integration of a DEA analysis engine:* This comprises both envelopment and multiplier DEA models, the input- and output-orientated methodologies as well as constant, variable, non-increasing and non-decreasing return-to-scale orientations. An existing linear programming dynamic link library (DLL) is utilised.
- *Performing all necessary case studies:* Case studies are performed for multiple thermal plants, allowing for the benchmarking of the target South African coal fired power plant against US plants of similar design. These case studies must make use of both classical and DEA-based efficiency evaluation methods, as well as regression techniques. Various classical efficiency methods as well as various DEA orientations are used, so as to examine which produces more accurate results in various contexts. Additional factors are incorporated into DEA case studies to establish if the process can provide additional insight into plant performance.
- *Analysing the results generated from case studies and deriving conclusions as well as making recommendations:* The results of efficiency tracking and comparative benchmarking case studies are used to identify potential areas where energy savings may be achieved. The

results of classical efficiency evaluation, as well as those of regression analysis are used to determine the extent to which additional factors can effect overall plant efficiency. The accuracy of regression analysis results is evaluated, as well as the method's usefulness when used for M&V baseline adjustments. The accuracy of the DEA-based plant efficiency tracking method is determined, as well as its usefulness as both as a tool for usage in M&V exercises and in plant diagnostics.

The major components of the project are represented visually in ***Figure 1-1***. These components include the design and implementation phase which covers the development of the relational database and the software application. The analysis and results component is also covered, which includes case study procedures as well as the formulation of results and conclusions. The final project component included is reporting.

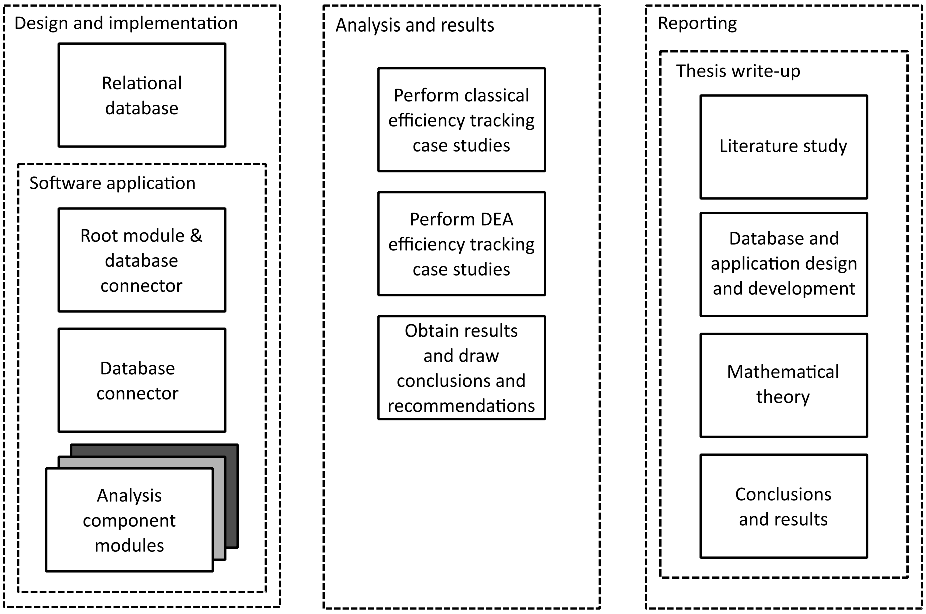


Figure 1-1: *Project components*

1.4 Document structure

This project document consists of six chapters as well as three appendices. The structure is summarised below:

- Chapter 1 comprises the project overview, project motivation and project description.
- Chapter 2 comprises a literature study which shows research in topics relevant to this project, such as coal fired power generation, measurement and verification, relational

databases, integrated development environments, software design, statistical methods for data validation, and previous research into DEA's use in power generation contexts.

- Chapter 3 comprises and examination of classical efficiency evaluation methods, including actual, technical and scale efficiencies, as well as heat rate, as well regression analysis in plant efficiency evaluation. An in-depth examination of Data Envelopment Analysis is performed, including the mathematical formulation of its various methodologies and model variations. These consist of the envelopment and multiplier models, input- and output-orientations, constant, variable, non-increasing and non-decreasing return-to-scale orientations.
- Chapter 4 comprises the development and implementation phase of the project, consisting of the design and implementation of a relational database and a software application.
- Chapter 5 comprises the results of the various case studies utilising classical efficiency evaluation, regression analysis, and DEA efficiency evaluation.
- Chapter 6 comprises the conclusions that can be drawn from the case study results as well as recommendations for subsequent future projects.

2 Literature study

2.1 Overview of literature study

The focus during this project is the development of a software application to analyse single and multiple plants' efficiency using both classical and Data Envelopment Analysis (DEA) theory. The following aspects are investigated:

- Coal fired power generation
    - Entropy and heat engine concepts
    - Plant operations and energy flow
    - Types of coal
    - Factors affecting plant efficiency
    - Methods to increase plant efficiency
    - Plant condition monitoring
- Measurement and verification
    - Energy efficiency and demand side management project stages
    - Measurement and verification methodology
    - Measurement and verification project stages
- Relational databases
    - Structures
    - Management systems and query languages
- Integrated development environments
- Software design
    - The unified modelling language
    - The unified process
- Statistical methods for data validation
- Previous work using DEA in power generation

2.2 Coal fired power generation

2.2.1 Overview of coal fired power generation

Thermal fossil fuel power plants make up the vast majority of installed capacity, providing over 99% of South African [7] and 81% of global generated electrical energy [17]. Most thermal power plants use coal as primary fuel, as coal is an abundant fuel source, with an estimated 990 billion tons of reserves available [4].

Coal's popularity stems from being a relatively common but energy-dense resource [18], making it the ideal fuel for large-capacity baseload electrical energy supply. However, in recent years coal has come under fire for being a major contributor to greenhouse-gas release as well as other emissions that negatively impact the surrounding environment as well as human health [11]. For these reasons many developed countries have began replacing aging coal plants with more modern clean-burning gas-fired plants [11]. However, at the time of writing, approximately 40% of global electrical power is still produced from coal fired power plants [11, 4], making developments and research in coal fired electrical generation far from irrelevant.

2.2.2 Entropy and heat engine concepts

Thermal plants, in their simplest form, consist of heat engines, which harness heat from a hot source, extract part of this heat as work and reject the rest assigning to a cold sink. Such an engine is illustrated in ***Figure 2-1*** [13].

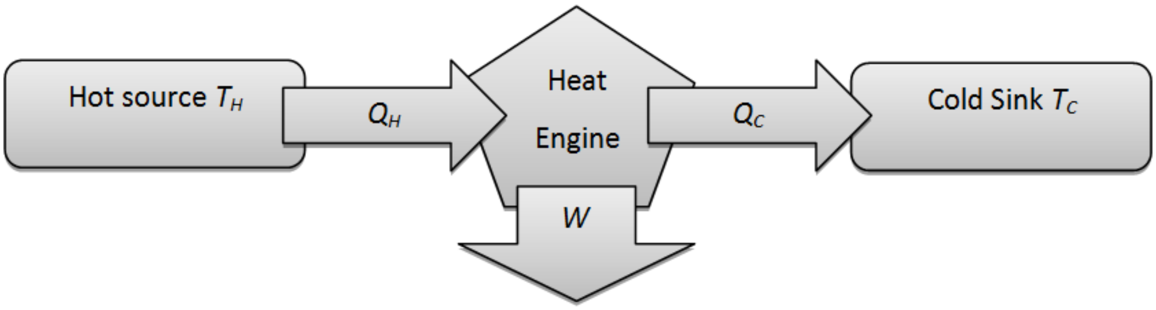


Figure 2-1*: Basic heat engine [13]*

In ***Figure 2-1***, T_H and T_C are the temperatures of the hot source and cold sink respectfully, while Q_H and Q_C represent the heat transmitted from the hot source to the engine and the heat transmitted from the engine to the cold sink respectively. W is the work done by the engine i.e. the portion of Q_C converted into usable energy [13]. According to the second law of thermodynamics, no heat engine can be 100% efficient, as some energy will always be rejected to the cold sink [19]. Thermal efficiency is calculated as in Equation (2.1).

$$Thermal\ efficiency = \frac{W}{Q_H} = \frac{Q_H - Q_C}{Q_H} = 1 - \frac{Q_C}{Q_H} \tag{2.1}$$

Entropy is defined as a measure of disorder or randomness when referring to the molecular nature of a system [19]. Unlike energy, which is conserved, entropy is seen to increase between processes. The loss of entropy (S) from a system is calculated as in Equation (2.2).

$$\Delta S = \frac{Q}{T} \tag{2.2}$$

In Equation (2.2) Q represents heat, T represents temperature and *ΔS* represents the change in entropy. To find the maximum theoretical thermal efficiency of a heat engine, Equation (2.2) is applied to the heat engine illustrated in ***Figure 2-1***. The work done, *W,* is assumed to be ideal and has no associated entropy. The entropy must increase between the hot source and the cold sink. This gives rise to Equation (2.3) [13].

$$\frac{Q_C}{T_C} \geq \frac{Q_H}{T_H} \tag{2.3}$$

Rearranging and substituting into Equation 2.6.1 gives Equation (2.4)

$$Thermal\ efficiency = 1 - \frac{Q_C}{Q_H} \leq 1 - \frac{T_C}{T_H} \tag{2.4}$$

Therefore the maximum theoretical efficiency is given in Equation (2.5)

$$\eta_{max} = 1 - \frac{T_C}{T_H} \tag{2.5}$$

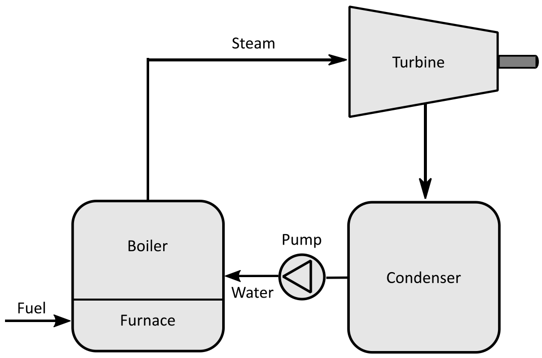
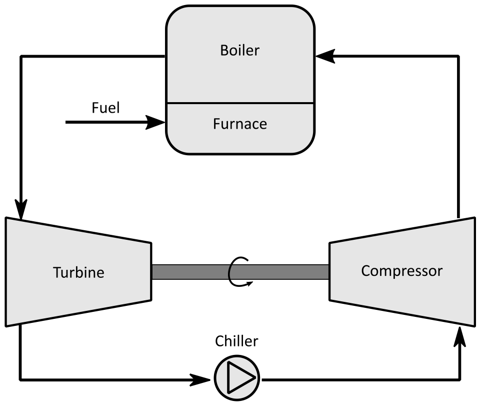
As is visible in Equation (2.5), efficiency increases with the temperature of hot source and decreases with the temperature of cold source. Thus, efficiency is increased by increasing the temperature of hot source or decreasing the temperature of cold source [13].

2.2.3 Coal fired power plant operation and energy flow

In thermal power plants heat is generated from burning fuel which is used to boil water and make steam, which in turn drives turbines. Most plants utilise either the *Rankine cycle* or the *Brayton cycle*. The differences between the two are illustrated in ***Table 2-1*** [13] [20].

Table 2-1*: Rankine and Brayton cycles [13] [20]*

	Rankine cycle	***Brayton cycle***
Typical usage	Baseload plants.	Peaking plants.
Economics	High initial cost, low running costs.	Low initial cost, relatively high running costs.
Operating fluid	Alternates between liquid and gaseous states.	Remains gas throughout cycle.

Cycle		

The Rankine cycle (and modifications on it) is most commonly used in coal fired power plants and thus major components are expanded on below.

2.2.3.1 Rankine cycle components and efficiencies

- *Coal handling, pulverisation and drying:* From a stockpile, coal is typically dried and pulverised, before being sent to the furnace bunker. Larger pieces of coal burn less efficiently, making pulverisation important [21]. Moist coal also burns less efficiently, as heat energy is taken to evaporate coal moisture [4]. Effective coal drying can increase plant efficiency by up to 1,7%, depending on the grade of coal [21]. The furnace can be seen as the hot source when viewing the plant as a heat engine.
- *Boiler:* Coal is burnt to heat the boiler, where water is converted into high -pressure steam. The process whereby heat is transferred to the water is known as *heat addition* [4]. Boiler losses tend to be relatively small, somewhere in the order of 10% to 20% [21, 13]. These inefficiencies are mainly caused by fuel not burning to completion and heat losses in plant emissions [13].
- *Turbine:* High pressure steam is used to drive a turbine. Plants may utilise more than one turbine on the same shaft (driving the same generator) operating at different steam pressures. Turbine wear and tear can cause significant decreases in efficiency. Typical steam turbine efficiency falls between 45% and 57% [22].
- *Condenser:* Once steam has passed through the turbine, it is sent to the condenser. Here it is cooled down and once again becomes liquid water. The condenser is sometimes cooled by air (known as dry cooling) but is usually cooled by water from a cooling tower, reservoir or the sea [13]. It can be seen as the cold sink when viewing the plant as a heat engine. The condenser creates a vacuum which draws spent steam out of the turbines. A deteriorated condenser may leak water or air, and will have a negative impact on overall efficiency, as the vacuum is lessened and thus steam is drawn less effectively from the turbine [21].

- *Electrical generator:* Converts the mechanical motion of the turbine into electrical energy. Generators, coupled with the transformers used to connect to the utility grid, generally have an efficiency of approximately 99% [13].
- *Auxiliary sub-systems:* These consist of the various minor components that supply the component listed above. All of these sub-systems consume auxiliary electrical power, usually drawing straight from the generating side of the plant. They may include [11, 21]:
    - *Induced draft fans:* used to create a negative pressure or vacuum, usually in a smoke stack.
    - *Forced draft fans:* used to create a positive pressure.
    - *Electrostatic precipitator*: removes fine particulate matter from emission gases using electrostatic charge.
    - *Feed-water heaters:* used to pre-heat water before being sent to the boiler.
    - *Air heaters:* used to preheat air before being sent to the furnace.
    - *Soot blowers:* remove soot and ash from furnace.
    - *Pumps, fans and conveyors.*

2.2.3.2 Rankine cycle entropy

Figure 2-2 shows an entropy diagram for a typical Rankine cycle [19]. At point 1, the operating fluid is liquid water. This is sent to the boiler and heat is added, increasing the temperature. The fluid is steam at point 2, saturated at a certain pressure. The steam enters the turbine and expands, reaching point 3. The steam is sent to the condenser, where it is cooled down and returns to liquid form at point 4. The liquid water is pumped to the boiler and the cycle repeats [19].

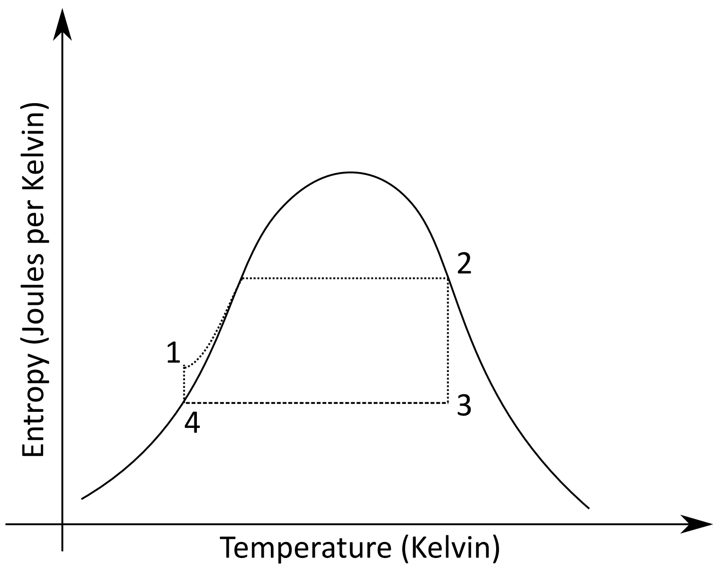


Figure 2-2*: Entropy diagram for typical Rankine cycle [19]*

2.2.4 Types of coal

Coal is a sedimentary rock made. up of organic and inorganic material and has been used for centuries as a fuel source [11]. Various classifications of coal exists and are covered below in brief:

- *Lignite:* Often referred to as brown coal or immature coal, lignite is soft with a high moisture content of up to 66%. Lignite has a typical calorific value of 10 to 20 MJ/kg and a carbon content of between 25% and 35% [11].
- *Sub-bituminous:* An intermediate quality coal, sub-bituminous coal usually has a calorific value of between 19 and 26 MJ/kg and a carbon content of 25% to 35% [11].
- *Bituminous:* Typically has an energy content of 24 to 33 MJ/kg. Carbon content is high, ranging from 45% to 86% [11].
- *Anthracite:* A mature form of coal with a carbon content of between 86 and 98%. Also called hard coal, anthracite has an energy value of approximately 35 MJ/kg [11].

2.2.5 Climatic, operating and design factors affecting plant efficiency

Thermal power plants are essentially heat engines (as described in section 2.2.2). This means that any factors affecting the temperature of the sinks or the transfer of heat between these sinks will have an effect on the overall efficiency of the system. These environmental factors consist of the following [4, 21]:

- *Ambient temperature:* increases the temperature of the condenser coolant (cold sink), thus decreases useful energy released (see ***Figure 2-1***) [21, 11].
- *Humidity:* humid air is denser than dry air, which means that airflow to the compressor is reduced with more humid air. This results in a lower concentration of oxygen in the turbine, which means that the amount of unburnt fuel increases and thermal efficiency decreases. Humidity especially affects evaporative cooling systems [23]. Humid air also decreases the heat-absorbing characteristics of air used in condenser dry-cooling systems [21].
- *Air pressure:* a lower air pressure leads to a lower concentration of oxygen, decreasing thermal efficiency, as described above [11].
- *Rainfall:* rain may increase the amount of moisture in coal. A higher fuel moisture content leads to a lower efficiency, as energy is used to evaporate moisture [11]. Adequate coal drying can minimise the negative effects of coal moisture.

Apart from the above environmental factors there are various operating and design factors that affect overall plant efficiency. These are listed below, along with their relevant methods that may increase overall plant efficiency:

- *Coal quality:* Coal with a higher calorific value is associated with higher plant efficiency, as it requires less processing and handling per MWh produced [11]. The quality of coal should be carefully monitored via accurate coal analysers, which measure moisture, calorific content, sulphur content, NO_X and carbon content.
- *Coal processing:* Pulverisers and conveyers draw auxiliary electrical energy to operate. Effective pulverisation can greatly increase plant efficiency.
- *Boiler:* Boilers should be inspected often, as leaks causing pressure losses result in greatly decreased efficiency. Furthermore, boilers should be very well insulated to minimise radiated heat. Air heaters in boilers can also greatly increase boiler efficiency, however these should be cleaned often and checked for acid erosion.
- *Plant capacity:* Plants with higher MW capacity ratings tend to be more efficient than smaller plants, as there are less losses in large scale equipment [11].
- *Soot blowing:* Soot is removed from the furnace to increase heat transfer. Although this is traditionally performed on a periodic basis, a conditional basis is preferred in current international best practice. Soot blowers should not be used unnecessarily, as they consume large amounts of auxiliary electrical energy.
- *Air heaters:* Air is pre-heated before being forced into furnace. Effective heating allows fuel to burn more effectively [13].
- *Plant generation configuration:* Rankine cycle, Brayton cycle, combined cycle etc. have varying efficiencies depending on plant context. Fuel heating in combined cycle systems greatly increases efficiency [13].
- *Plant cooling configuration:* Closed-circuit, evaporative, once through, dry and coastal cooling water systems have varying efficiencies. Heat recuperation from cooling systems also increases plant efficiency [4, 21]. In wet cooling systems filtration and/or reverse osmosis can be used to decrease the mineral content of cooling water, which in turn increases its heat carrying quality.
- *Use of reduced NO_x cycles in coal plants* consumes additional air and increases the amount of unburnt fuel [24].
- *Air filtration and silencing* cause pressure losses in the system, resulting a lower efficiency [23]. Electro-static precipitators remove particulate from released gases, but also consume auxiliary energy.
- *Capacity factor/load factor:* Refers to the instantaneous ratio of the plant's rated maximum generating capacity to the generating capacity at which the plant is operating. A plant tends to become more efficient at higher capacity factor values [4].

2.2.6 Condition monitoring in power plants

The accurate measurement of plant data, such as fuel consumption, fuel calorific value, sent-out electrical energy, temperature and pressure of various subsystems, emissions and auxiliary electrical energy consumption, requires complex monitoring equipment [25]. However, this data is required to track plant heat rate, maximise efficiency and reduce required maintenance [26]. Advanced condition monitoring systems are usually absent in older plants and are very expensive and difficult to retrofit [25].

2.3 Measurement and verification

2.3.1 Overview of measurement and verification

Energy Efficiency and Demand Side Management (*EEDSM*) are increasingly relevant activities, aimed at decreasing the demand on electric utilities for environmental and financial reasons. *EEDSM* projects depend heavily on accurate measurement and evaluation of interventions [6]. Typical project stakeholders include:

- *Power utility*
- *Project client*
- *Energy service company (ESCo)*

Measurement and Verification (M&V) is the name given to the process whereby project performance is evaluated and communicated to these stakeholders in a manner that is both objective and independent. The M&V process reduces the level of risk to stakeholders and encourages additional investments in *EEDSM* projects [5] [6].

2.3.2 Typical energy efficiency and demand side management project stages

In this section the typical stages found in an *EEDSM* intervention project are covered. The ESCo should adhere to the 8 steps shown in ***Figure 2-3*** [6].

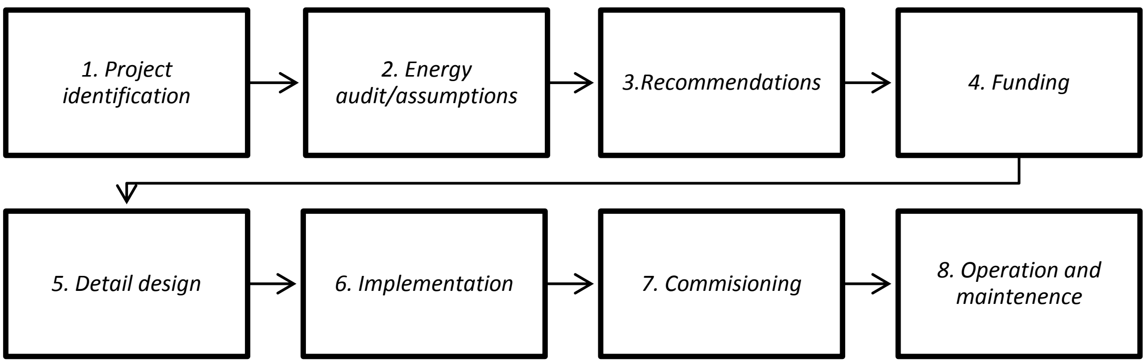


***Figure 2-3**: Typical energy efficiency and demand side management project stages [6].*

The project stages shown in ***Figure 2-3*** are expanded on in ***Table 2-2*** [6].

***Table 2-2**: EEDSM project stage details [6].*

1. Project identification	• Client or ESCo identifies potential for EEDSM project. • Client contracts ESCo to establish potential savings and financial impact. • Client provides letter of intent to ESCo.
2. Energy audit/assumptions	• Energy audit is performed. This usually consists of both a brief observational visit and a more detailed examination. • Potential savings of impact are estimated by establishing the number, type and rating of all relevant energy consuming devices. • Any non-measurable factors that may impact measurements are taken into account as assumptions.
3. Recommendations	• After all relevant information is gathered, the ESCo provides the client with recommendations as to which EEDSM efforts should be pursued. • After the client has accepted these the utility is provided with a proposal for project funding.
4. Funding	• Once the utility has determined that the proposed EEDSM project will provide adequate results within an acceptable time frame and at reasonable risk, funding is granted.
5. Detail design	• Following project approval the ESCo produces a deliverable documenting the complete design process of the project, as well as expected results.
6. Implementation	• Physical implementation of all steps listed in ESCo's design document. Demand typically fluctuates in this stage, as is shown in ***Figure 2-4***. • M&V performance assessment begins during this stage (see section 2.3.4).
7. Commissioning	• ESCo commissions installed equipment after implementation to confirm correct installation.
8. Operations and maintenance	• System maintenance is performed either by ESCo or client. The ESCo is held liable for decreases in system performance during an agreed initial period. Liability for failure falls on the client after this period.

2.3.3 Measurement and verification methodology

M&V, in its most simple definition, measures the energy savings of an EEDSM intervention. This is done by measuring energy usage and demand before and after the completion of the intervention [5]. This is shown in Equation (2.6) [6].

$$Savings = (E_{pre-implementation} - E_{post-implementation}) \pm Adjustments \qquad (2.6)$$

In Equation (2.6) $E_{pre\text{-}implementation}$ represents the baseline energy use i.e. before the completion of the EEDSM intervention while $E_{post\text{-}implementation}$ is the energy use after the intervention. *Adjustments* accounts for any external factors that may have had an effect on operating conditions, such as weather or building occupancy [5]. Equation (2.6) is illustrated visually in Figure 2-4 [5].

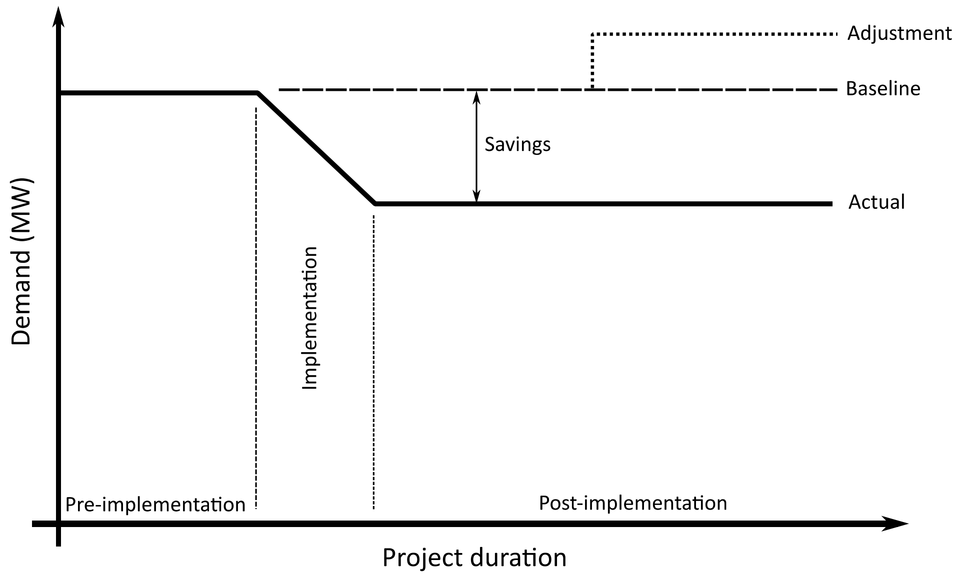


***Figure 2-4**: Visual representation of Equation (2.6) [5].*

There are four options that M&V teams may make use of in EEDSM interventions. These are listed below and summarised in Figure 2-5 [5] [6].

- *Option A: Retrofit isolation with primary measurements:* Partial measurement of retrofitted equipment, important parameters are measured while others are estimated.
- *Option B: Total retrofit isolation:* Like *Option A* but with all relevant parameters measured.
- *Option C: Whole building:* Saving calculated from measurements taken from the entire facility where EEDSM intervention is performed.
- *Option D: Calibrated simulation:* computer simulation is used to estimate overall savings. The simulation is “calibrated” with facility billing data.

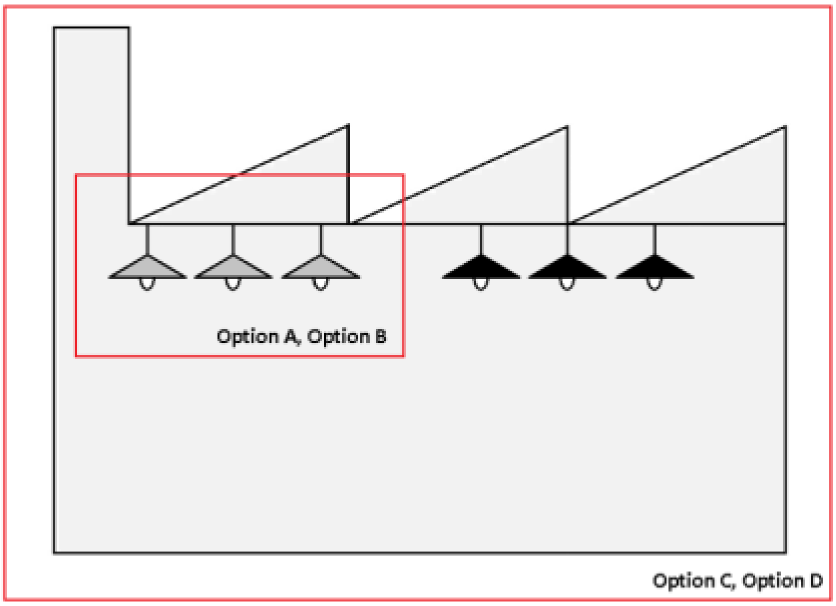


***Figure 2-5**: Visual summary of M&V options [5] [6].*

The following points are taken into account when selecting an M&V option [5]:

- *Intervention costs and projected savings:* the extent of M&V activities and potential savings should be proportional to the total project cost.
- *Complexity of intervention project:* a higher complexity system requires a more intricate M&V approach.
- *Number of associated projects in facility:* in the case of multiple EEDSM projects in a single facility, the measurements may be related. Thus, measurement equipment may be shared or re-used.
- *Risk or uncertainty associated with the project:* uncertainty in a project brings with it a requirement for more inclusive and accurate M&V procedures to provide adequate communication to shareholders.
- *Responsibility allocation between stakeholders*: certain stakeholders may insist on a more thorough evaluation if they are held liable for project shortcomings.
- Additional uses for measurement equipment or measured data.

2.3.4 Typical measurement and verification project stages

An M&V intervention plan needs to be clearly communicated by the M&V team to the other stakeholders to avoid ambiguity. These parties review and, if satisfied, accept the plan. Figure 2-6 shows the typical steps in an M&V process [6]. It should be noted though that there may be various iterations of each step, depending on stakeholder input or approval.

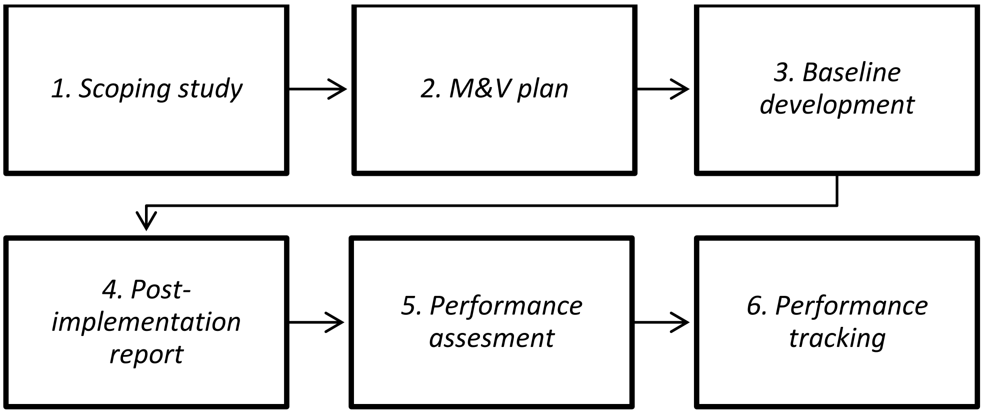


Figure 2-6: *Summary of M&V project structure [6].*

Table 2-3: *Summary of typical M&V process [5] [6].*

1. Scoping study	M&V team must produce a scoping report deliverable, comprised of the following details [5]: • Project information such as contact details of all stakeholders. • Project objective. • Description of project site. • Relevant facility tariff structure. • System audit: includes detailed information of system targeted by EEDSM intervention. • Proposed ESCo activities. • ESCo expected results. • Project evaluation. • Conclusion and comments.
2. M&V plan	M&V team must produce a M&V plan deliverable comprised of the following details. Once again, stakeholders must approve the document. The following must form part of the report [5] [6]: • Project information. • Project objective. • Description of project site. • Relevant facility tariff structure. • System audit. • Proposed ESCo activities. • Assumptions. • Evaluation and expected results. • Selected M&V option: as in section 2.3.3. • Boundaries of EEDSM intervention savings. • Baseline characterisation i.e. how the baseline was calculated. • Baseline adjustments. • Pre- and post-implementation metering plan. • Savings calculation methodology. • Condonable periods. • Handling of last data.
3.Baseline development	M&V team must produce a baseline report deliverable to primarily communicate the pre-implementation energy usage of the EEDSM project. The following must form part of the report [5]:

	• Project information, project description and site description (as above). • Baseline variables. • Metering data, period and interval used to establish baseline. • Data used. • Characterisation procedures. • Baseline service level adjustments. • Adjustment procedures. • Data for use in savings calculations. As before, all stakeholders must approve the report.
	Project Implementation
4.Post-implementation report	M&V team must produce a post-implementation report deliverable after EEDSM intervention has been completed to primarily confirm that that the ESCo has successfully completed all contracted tasks. The report must contain the following [5]: • Project information, project objective and site description (as above). • Pre-implementation system. • System changes that include proposed and actually implemented changes, as well as the deviation between them. • Additional comments.
5.Performance assessment	M&V team must produce periodic performance assessment reports over a period of 3 months to monitor system performance. In the case of the EEDSM intervention not meeting its contractual targets, this period allows the ESCo to make any necessary changes to avoid liability. The performance assessment reports must include the following [5]: • Project information (as above), report author's details, and reporting period. • Project savings relevant to baseline values. • Environmental impacts. • Relevant period demand and consumption data. No performance assessment reports may be submitted unless all stakeholders have approved the project baseline report [6].
6.Performance tracking	M&V team must produce a deliverable summarising all savings relative to baseline per reporting period. These reports are provided on agreed intervals throughout the entire duration of the M&V project. Performance tracking reports communicate both the project savings and whether or not these savings are maintained over time [6]. During this phase the client is held liable for any shortcomings in project performance [5].

2.4 Relational databases

2.4.1 Overview of relational databases

A database can most simply be defined as a collection of logically coherent related data [30]. Databases are created and populated for a specific purpose with a narrow group of intended users who have a common interest in a specific application [30]. Relational databases store data in such a way that they are easy to use and search, making them ideal for use in scientific studies as file systems [28]. In this section relational database structures, languages and software platforms are discussed.

2.4.1 Database normalisation

The concept of the relational database was first developed by E.F. Codd in 1970, who intended to develop an efficient relational model for data [29, 30]. Codd developed the first normal form of a relational database (and later the second and third) [30], which first introduced the concept of normalization. In database design, normalisation refers to the process whereby the tables, tuples and attributes are arranged to minimise redundancy [30]. This often entail the isolation of data in separate tables that are related in some way, allowing for easy modification of data from a single entry.

Codd defined the following objectives for the first normal form normalisation process [29, 31]:

- *To remove any instances of unwanted data dependencies.*
- *To minimise the database restructuring when additional data is included.*
- *To make the relational database model more explanatory to users.*
- *To remove any effect of time-varying query statistics.*

2.4.2 Relational database structures

The primary purpose of relational databases is the storage of data in tables, known as relations.. This data is grouped into tuples, which make up the rows of the relations [28]. These tuples are unique i.e. each tuple consists of a number of attributes, which make up the columns of the relation. Every relation includes a unique attribute known as the Primary Key (PK), which is used purely for identification purposes. The relation structure, including tuples and attributes, is summarised in Figure 2-7 [28].

	Attribute 1	*Attribute 2*	*Attribute 3*	…	*Attribute N*
Tuple 1				…	
Tuple 2				…	
Tuple 3					
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
Tuple N				…	

Figure 2-7*: Visualisation of typical relation [28].*

2.4.2.1 Primary and foreign keys

Often attributes in a relation may point to attributes in a separate relation, creating a link between the two. These links do not need to be unique, as multiple tuples in one relation may refer to the same tuple in another relation [32]. These tuples must be PKs. Attributes that point to PKs in separate relations are called Foreign Keys (FK). This is illustrated in the example in Figure 2-8 [32].

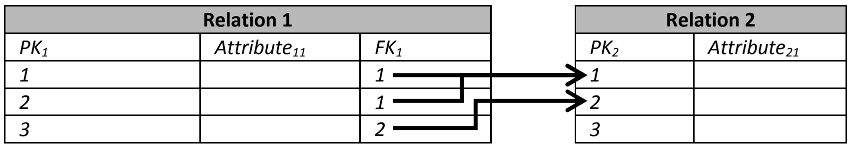


***Figure 2-8**: Visual representation showing PK and FK operation [32].*

2.4.2.2 Link tables

Link tables refer to relations that link two or more other relations together in a manner similar to that used by PKs and FKs. The use of link tables allows for the easy repurposing, modification and expansion to the structure of an existing database, which brings the database in line with Codd's objectives from section 2.4.1.

A link table will typically have a primary key attribute, like most other relations, and two foreign key attributes. These point to the parent and child relations respectively, as illustrated in ***Figure 2-9***, where *Parent ID* and *Child ID* are the foreign keys connecting the parent relation (*Relation 1*) to the child relation (*Relation 2*).

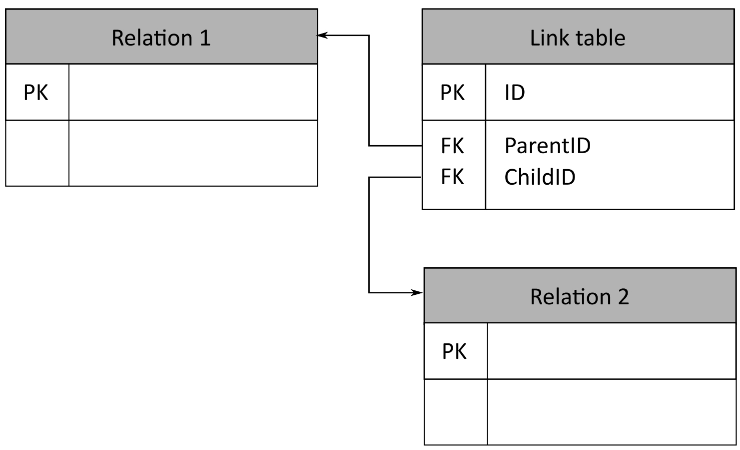


***Figure 2-9**: Link table structure.*

While PKs and FKs are specific in their connections, link tables can easily be altered to point to different parent or child relations, allowing a relational database to be modified with significantly less effort.

2.4.3 Database management systems and query languages

The purpose of database management systems (DBMSs) is to allow for the simple retrieval of data from a database, as well as to allow for the creating, populating and management of relations [32]. This is accomplished through queries to the relevant database. Searching for data requires significantly less computational resources when utilising a DBMS. Additionally, DBMSs make sharing data between multiple users possible.

It is generally undesirable to query a database using general programming languages, as these are inefficient and time consuming. Therefore a Query Language (*QL*) is used. The *QL* allows for the querying of databases without ambiguity. The user does not need to specify how a query is executed or possess technical knowledge of the database, they only needs to know which results are expected [32].The DBMS usually evaluates queries in an algebraic manner [29]. Currently there are a number of commonly used *QL*s, some examples of which are listed below [33]:

- *SQL*
- *LINQ*
- *ScalaQL*
- *SchemeQL*

MySQL was selected for use as the database platform in this project as it is the most commonly used database system available and, as such, has an extensive base of support and literature available [33]. Although it is very fast and durable, *MySQL* is open-source, which is preferred in this project. The platform utilises SQL, the most widely used QL [33]. Furthermore, *MySQL* is easily scalable and can handle small or large datasets with equal ease [33].

2.4.4 WAMP server

Windows Apache MySQL Php (WAMP) server is selected to host the database used in this project. WAMP is used to host a server locally on Microsoft® Windows™ operating system, which allows for easy testing and development of both the project database and the project software application. Additionally, WAMP is freely available, making it ideal for use in this project.

2.5 Integrated development environments

2.5.1 Overview of integrated development environments

An Integrated Development Environment (*IDE*) is the name given to a software platform that allows for software development via a user friendly Graphical User Interface (*GUI*). An *IDE* allows for rapid application development, making it ideal for use in this project. An *IDE* should fulfil the following roles in this project:

- Applications must be based in Microsoft® Windows™ operating system, to allow for maximum portability.
- Applications must support database connectivity.
- Applications must allow for the development of a user friendly *GUI*.

A few examples of commonly-used IDEs for Microsoft® Windows™ are listed below:

1. *Microsoft® Visual Studio™:* Often used to develop .NET code. User codes in C or C++ [34].
2. *Eclipse:* An open source package that allows the user to code in multiple languages, including Python, C++ and JavaScript. Also ideal for development in Google® Android mobile operating system [35].
3. *Embarcadero® Delphi™:* A rapid application development platform with extensive database focus. The user codes in Object Pascal language. An included large Visual Component Library (VCL) allows for the easy development of user-friendly *GUI*s [36].

The required software application is database focused, and therefore Embarcadero® Delphi™ was selected. Additionally, Delphi™ has an integrated debugger and automatically generates Microsoft® Windows™ .EXE executable files, which allows for portability between users and simplifies testing [36]. Delphi™ also includes built in support for XML. The Embarcadero's® DBExpress data driver is used, as it allows for very fast access and can integrate with a large number of databases, including *Oracle, Firebird* and *MySQL* [37].

For the Linear Programming (LP) aspect of the project, an existing library must be utilised, as the development of a LP solver will be time-consuming and unnecessary. Rather than using a separate package for this process, such as MATLAB, Microsoft® *Excel*'s™ SOLVER add-in, or Python's *NumPY* mathematics library, it is preferred to use a library which can be directly accessed by Delphi™. A dynamic-link library (DLL) is a file that acts as a library for functions, classes, variables and resources that are easily shared between modules. A DLL cannot be run directly and must be opened by a separate executable file [38]. A DLL is easily called from an IDE [39]. There are numerous LP DLLs available, however the most widely utilised and documented is *lp_solve.*

Lp_solve is a mixed integer LP solver DLL, with no limitation to model size. The library is freely available open-source, subject to GNU Lesser Public License [39] [40]. *Lp_solve*was originally developed by Michel Berkelaar from Eindhoven University of Technology and expanded by Jeroen Dirks, Kjell Eikland and Peter Notebaert [39]. Version 5.1 of *lp_solve* is the most widely available and well documented and, as such, was selected for use in this project. Additionally, a Delphi™ class developed for the *lp_solve* DLL by *Henri Gourvest* is utilised[1].

2.6 Software design

2.6.1 Overview of software design

In this section the methodologies utilised in the design and implementation of the software application developed in this project are covered. The unified modelling language and the unified process are the two primary methodologies employed and are covered in sections 2.6.2 and 2.6.3 respectively.

2.6.2 Unified modelling language

The Unified Modelling Language (UML) is a general-use system design process in the field of software engineering. UML is included in this study as the project includes the development of a software application, the design of which is based on the UML framework. UML is ubiquitous in its field and is often described as the industry standard, making it the best choice for this project [41]. It should be noted that UML is not a development method, but rather a method of visualising system architecture and documenting its development [42]. The 4 major goals of the UML process are [41]:

- To *visualise*
- To *specify*
- To *construct*
- To *create*

UML was developed by Booch, Jacobson and Rumbaugh between 1994 and 1996. The process framework is a combination of three pre-existing methods, namely the *Booch* method, the *Object-modelling technique* and *Object-oriented software engineering* [41]. UML was intended by its creators to be used only for object-oriented software development, but its versatile nature allows for its use in many more contexts.

UML describes a system as a combination of various models, where each model consists of multiple diagrams and documentation. Each model is thus a description of a separate aspect of the same

[1] *Lp_solve v5.1 API for Delphi v5,6,7 & FPC compiler v1.9.x, LGPL License, Henri Gourvest 2004.*

complete system. Diagrams are largely utilised in UML. The nine diagrams used in this process are summarised below [41].

- *Class diagrams* include classes, interfaces and collaborations. Also included are their interactions.
- *Object diagrams* include all objects and their interactions. They provide insight into inner structure of class diagrams.
- *Use case diagrams show* interactions between various users and the system.
- *Interactions diagrams* show the dynamic interactions between objects.
- *Sequence diagrams* are interaction diagrams that focus on the time-wise ordering of interactions.
- *Statechart diagrams* show the system as a state machine and its states, transitions, events and actions.
- *Activity diagrams* are statechart diagrams that show the flow of events and activities within the system.
- *Component diagrams* show the structure and dependencies between components.
- *Deployment diagrams* show the workings of run-time processing structures and their associated components.

2.6.3 The unified process

The Unified Process (UP) framework is used in the design phase of a project. Its primary use is to guide all project elements of the design process, focusing on the necessary inputs and outputs of an activity. However, the means whereby these inputs and outputs are accomplished are unrestricted and can be accomplished by any means [41] [42]. The UP's main goals are to establish:

- The responsibilities of individuals involved in a project.
- The time frame of project activities.
- How each project activity achieves its goals.
- The inputs and outputs allocated to each project activity [42].

2.6.3.1 Key elements of the unified process

The UP is defined by four key elements, listed below. The process must be:

- Iterative and incremental,
- Case-driven,
- Centred around system architecture, and

- Sensitive to associated risks [42].

The UP does not attempt to complete the entire design in a single take. Rather, the process consists of multiple iterations, reviewing and modifying each project stage multiple times [41]. This allows potential risks to be identified and prevented or minimised. Cases are used to establish the primary system requirements. By constantly keeping these cases in mind, UP ensures that each increment of the complete system stays relevant to the initially specified user requirements [42].

If a project is divided among individuals it is often difficult to keep track of the architecture of the complete system. UP acknowledges the architecture as the "skeleton" of the system and as crucially important in the development process, attempting continual refinement in subsequent system iterations [42]. UP highlights unknown elements of the system, making it possible to address potential threats to the process early on.

2.6.3.2 Life cycle phases of the unified process

UP consists of 4 separate life cycle phases, each centred on a separate aspect of the design of the system. These phases are inception, elaboration, construction and transition [41].

During the inception phase the business case and project scope are established. Project feasibility is also covered [41]. The end result of this phase is the final vision for the system, which includes a basic use case model and elementary architecture plan. Also included are the most prominent project risks [42]. During the elaboration phase the functional requirements of the system are established. Additionally, the system architecture is created, the problem domain is analysed and the project plan is developed [41]. The construction phase is centred around the design and implementation of the system. The product of this phase is a completed "beta release" of the software [42]. During the transition phase the final product is released to the user. Required lifetime maintenance also falls under the transition phase [42].

2.6.3.3 Unified process disciplines

Although the phases covered in section 2.6.3.2 make up the primary structure of the UP methodology, there are 5 major disciplines that govern the entire process. These disciplines are not assigned to unique phases but rather can stretch between separate phases. The disciplines can be viewed as describing how project activities are related to each other [42].

The requirements discipline is focused on the activities that identify all requirements of the system, both functional and non-functional. The creation of the use-case model is the primary goal of this discipline [42]. The requirements identified in the previous discipline are now restructured in terms of the software to be developed. This is done in view of the analysis discipline. The detailed project design is the focus of the design discipline. The implementation discipline focuses on the actual coding of the software, as well as the compilation and documenting of the software [42]. The extent to which the product meets user requirements and product reliability forms the basis of the test discipline. The actual tests are described in detail.

The UP disciplines often overlap and run concurrently through the 4 life cycle phases described in section 2.6.3.2, however, it should be noted that they can be assigned to separate individuals despite this.

2.7 Statistical methods

2.7.1 Overview of statistical methods

In this project statistical methods are employed to examine and evaluate result data. These methods provide a metric whereby predicted data's "goodness" is measured, allowing the accuracy of the model performance to be evaluated.

2.7.2 Coefficient of determination (R^2)

The coefficient of determination, or R^2, is a statistical metric that measures how well predicted data fits an actual value, which is either forecast or calculated from a regression [43]. The mean of observed data is calculated as in Equation (2.7).

$$\bar{y} = \frac{1}{N}\sum_{i=1}^{N} y_i \tag{2.7}$$

In Equation (2.7) N denotes the sample size, y_i denotes the i^{th} observed actual value and $\bar{y}$ denotes the mean of all observed values. To calculate the R^2, it is first necessary to calculate the total sum of squares and the sum of squares of residuals, as shown in Equation (2.8) to (2.9).

$$SS_{total} = \sum_{i=1}^{N} (y_i - \bar{y})^2 \tag{2.8}$$

$$SS_{residual} = \sum_{i=1}^{N} (y_i - f_i)^2 \tag{2.9}$$

N denotes the sample size, SS_{total} and $SS_{residual}$ denote the total sum of squares and the residual sum of squares respectively, $\bar{y}$ denotes the mean of observed values, y_i denotes the i^{th} observed actual value and f_i denotes the i^{th} forecast value. Using the total sum of squares and residual sum of squares, the R^2 value can be calculated as in Equation (2.10) [43].

$$R^2 = 1 - \frac{SS_{residu\ al}}{SS_{total}} \tag{2.10}$$

2.7.3 Root mean square error

The Root Mean Square Error (RMSE) is widely used as the standard statistical metric to forecast accuracy, especially in climate and meteorological fields [44]. The RMSE is calculated as in Equations (2.11) to (2.12) [44, 45].

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N} E_i^2} \tag{2.11}$$

$$E_i = y_i - f_i \tag{2.12}$$

In Equations (2.11) and (2.12) N denotes the sample size, y_i denotes the i^{th} observed actual value, f_i denotes the i^{th} forecast value and E_i denotes the error between the actual and predicted values. The predictor can thus be assessed on its complete RMSE score, as each error will contribute to the final value. It should be noted though that each error increases the final RMSE score proportionally to its square, rather than its magnitude, resulting in outliers having a significantly larger effect on the final score [45].

2.7.4 Mean absolute error

The mean absolute error (MAE) is a statistical metric that serves as an alternative to the RMSE metric. The MAE is defined as in Equation (2.13) [44, 45].

$$MAE = \frac{1}{N}\left|\sum_{i=1}^{N} E_i\right| \tag{2.13}$$

In Equation (2.13) N denotes the sample size and E_i denotes the error between the actual and predicted values. The MAE has the advantage over RMSE in that outliers are not weighted as heavily and do not affect the final score as dramatically [45].

2.7.5 Correlation

Correlation is the name given to a unitless metric that serves to indicate to what extent two variables are related and it is used as a measure of dependence. Correlation indicates both the magnitude and direction of the relationship [43]. Assuming it is desired to calculate the correlation between two vectors $\boldsymbol{x}$ and $\boldsymbol{y}$. Correlation is calculated as in Equation (2.14) [43].

$$correlation = \frac{\sum(x - \bar{\bar{x}})(y - \bar{\bar{y}})}{\sqrt{\sum(x - \bar{\bar{x}})^2 (y - \bar{\bar{y}})^2}} \tag{2.14}$$

In Equation (2.14) $\bar{x}$, $\bar{y}$ denotes the expected value for the $\boldsymbol{x}$ vector and $\boldsymbol{y}$ vectors respectively.

2.7.5.1 Interpretation of correlation values

The strength of correlation varies between 1 and -1, a perfect positive and negative correlation respectively. A correlation value of zero indicates no correlation at all. The various interpretations of correlation values are shown in ***Table 2-4***.

Table 2-4*: Interpretation of correlation values [46].*

Value of correlation	*Interpretation*
1	Perfect positive correlation.
0.7 to 0.9	Strong positive correlation.
0.4 to 0.6	Moderate positive correlation.
0.1 to 0.3	Weak positive correlation.
0	No correlation.
-0.1 to -0.3	Weak negative correlation.
-0.4 to -0.6	Moderate negative correlation.
-0.7 to -0.9	Strong negative correlation.
-1	Perfect negative correlation

2.8 Data envelopment analysis in plant efficiency evaluation

2.8.1 Overview

In this project Data Envelopment Analysis (DEA) is proposed and evaluated as a power plant efficiency tracking method. The process is also used as to comparatively evaluate plants. This section discusses previous examples of DEA's use in power plant efficiency analysis. The process has been used before to evaluate multiple plants comparatively.

2.8.2 Other authors' findings in thermal power plant DEA efficiency

DEA was first applied to electrical generation by Färe *et al.* in a 1983 paper where the examined the relative efficiencies of Illinois plants [47]. The study aimed to examine the results of newly introduced regulations on state generation plants. They concluded the paper by hypothesising that regulations do not always result in increased plant efficiency or plant consistency [47].

In their 2010 paper, Baheera, Dash and Farooquie analysed the performance of 74 Indian coal and lignite fuelled power plants using DEA. Their analyses used five years of data They selected the BCC model as their Return-To-Scale (RTS) orientation [48]. Electrical generation was used as the sole output. Their analysis considered plant MW capacity as an input, which they describe as "a proxy for capital cost" [48]. In terms of operational data, forced outage and planned maintenance were used as inputs. Auxiliary plant energy consumption was used as an input, as well as average coal calorific content. Interestingly, input energy was excluded [48]. Their analysis identified ten plants that occupied the efficient frontier over all five years. They also concluded that a capacity slack of 10GW existed. DEA often produces less useful results when more DMUs are included, as a greater portion are viewed as efficient [10]. However, this was not the case in this study. They suggested the DEA method be used to set more realistic goals in carbon emissions reduction [48].

Lam and Shiu used DEA to analyse 30 Chinese thermal plants in different regions of the country over two years in their 2001 paper [9]. They included total energy input, plant MW capacity and number of employees as inputs, while their only output was generated electrical energy. DEA results were analysed using a regression analysis, where the authors investigated the various effects of other variables. They concluded that their results showed no excess capacity, but found that environmental factors had significant effects on efficiency scores [9]. Furthermore, they found plants that used diesel generators and larger units to be far less efficient [9]. The authors cover the economic aspects of their findings in detail, describing the ability of the DEA method to "allow regulators to formulate policies on deregulation and privatization, and to determine the appropriate productivity factor when imposing price-cap regulation or yardstick competition on electric utilities [9]".

In their 2011 article, Yang, Wang, Wen and McGill evaluate all plants of a Chinese power utility together from 1991 to 2008. Their main aim was to establish if efficiency had increase in later years and thus the years of the analysis are used as DMUs [49]. Their outputs included the average heat rate and capacity factors of all plants, while their inputs included installed capacity per capital, labour efficiency, operating expenses and energy loss. While the authors did confirm an increase in efficiency in later years, they concluded that their findings were "less robust in offering referential ways on how to improve power plants' efficiency" and only "provided...modest support for restructuring" [49].

Korhonen and Luptacik attempted to incorporate eco-efficiency into a conventional DEA in their 2004 paper [50]. Their work was done in support of a emission reduction programme in 24 European plants. Plants were evaluated before and after implementation of emission reduction technologies. Their analysis used capital cost as input, and used sulphur NO_x and particulate emissions as undesirable outputs. Their results were compared to the technical efficiency of the plant [50]. They found that plants with higher technical efficiency also showed a higher eco-efficiency and also clearly showed where savings had been achieved in emission reduction efforts [50].

Park and Lesourd determined the efficiencies of 64 different South Korean thermal power plants. Their analysis included the fuel input, labour and MW capacity as input and generated energy and capacity factor as outputs [51]. They suggested that the results of their DEA could be used as " exogenous variables into a standard econometric production function model" [51]. Thus, while plant efficiency has been evaluated over time using DEA, this has only been done using multiple plant datasets on a yearly basis and, to the author's knowledge, not on shorter time periods.

2.8.3 Variations on power generation efficiency DEA

Some authors have taken alternative approaches to evaluating power generation efficiency, often in place of energy efficiency. Chen, Yeh and Lee performed a DEA on the total electrical generation usage and production data of 73 different countries, using the countries as DMUs [52]. This study included CO_2 emissions as a non-desirable output, but also considered technical efficiency. THey found Asian plants to be superior to European and American plants, both in terms of technical and environmental efficiency [52].

The DEA process has been used in studies on renewable generation as well, although to a lesser extent. Iglesias, Catellanos and Seijas used the process evaluate the performance of 22 European wind farms [53] while Yokoto and Kumano used DEA to assess the suitability of various sites for future solar farms [54].

2.8.4 Inputs and outputs

The usefulness and accuracy of DEA is largely dependent on the choice of inputs and outputs selected for use in the analysis. DEA's major advantage over an actual efficiency analysis lies in its ability to include any measurable factor deemed relevant. Thus, most authors attempt to combine energy, operational and environmental data to gain an efficiency metric that considers more than just energy input and output datasets. For thermal power plant evaluation the most common Inputs in the literature examined are MW capacity, fuel energy input, and plant labour while the most commonly occurring outputs are generated electricity and capacity factor.

3 Theory of efficiency evaluation

3.1 Overview

This chapter presents and discusses the methods and theory used in the evaluation of power plant efficiency. The various concepts and terms associated with efficiency are discussed, as well as the classical methods of efficiency evaluation. Data Envelopment Analysis (DEA) is covered in depth.

3.2 Classical energy efficiency evaluation

3.2.1 Overview

This section presents the theory and methods relevant to classical methods of power plant efficiency evaluation. The various efficiency terms are also explained to remove any ambiguity.

3.2.2 Efficiency terms

When working with efficiency in its various forms it is important to distinguish between *actual, technical* and *scale efficiency.* In its simplest and most common form, efficiency (η) is defined as the ratio in Equation (3.1) [55].

$$\eta = \frac{\Sigma\ output}{\Sigma\ input} \tag{3.1}$$

Equation (3.1) gives the *actual efficiency* of a system. It can be thought of as the ratio of useful energy output to total energy input. For example, if a power plant consumes 1000MJ worth of fuel and outputs 320MJ of electrical energy, it can be seen to be 32% efficient, according to Equation (3.1).

Technical efficiency is a different efficiency measure that takes into account how well inputs are processed to produce outputs and how much in the way of excessive resources is consumed. The maximum possible result is referred to as the *efficient frontier*. Returning to the previous example, if a power plant is designed for an output of 1200MW but is operating at 900 MW its technical efficiency is calculated as in Equation (3.2) [10] [56]. The plant is thus deemed inefficient and its efficient frontier will be an output of 1200MW. This method is related to the *capacity factor* of the plant, which is calculated similarly [10].

$$technical\ efficiency = \frac{900\ MW}{1200\ MW} = 75\% \tag{3.2}$$

Scale efficiency is the term used when referring to the efficiency measure relating to volume. A system may be more or less efficient at an optimum size [10]. This is illustrated via an example in ***Table 3-1*** [10].

***Table 3-1**: Scale efficiency example [10].*

Plant	*Capacity*	*Actual efficiency*	*Scale efficiency*
Plant A	3600 MW	40%	$\frac{40\%}{40\%}$ =100%
Plant B	1200 MW	30%	$\frac{30\%}{40\%}$ =75%

If the plants are compared, it can be seen that Plant A is the more efficient of the two. It thus has a scale efficiency of 100%. Plant B's actual efficiency is taken as a ratio of the more efficient Plant A's actual efficiency, producing its scale efficiency results.

3.2.3 Plant efficiency evaluation methods

Plant efficiency can either be measured in terms of its individual component (boiler, turbine, etc) or in terms of the whole facility [4]. The efficiency of a power plant is often expressed as the *heat rate*. This is the measure of the amount of thermal energy input required to generate 1 kWh of output. The thermal input can be given in Btu or kJ. Equation (3.3) shows how the heat rate is calculated [13].

$$Heat\ rate\ (KJ/kWh) = \frac{3600}{\eta}(kJ\ per\ kWh) \tag{3.3}$$

Heat rate can be seen as the ratio of thermal energy input to electrical energy output. Heat energy is more commonly measured in joules or kilojoules, while electrical energy is more commonly measured in kWh, hence the different energy metrics. A lower heat rate is associated with a higher efficiency. The first power plants had heat rates of about 74000 kJ/kWh (approximately 5% efficient) [13], while a typical present day plant has a heat rate of about 11600 kJ/kWh (approximately 30%).
Actual efficiency ratio can also be used to evaluate plant efficiency. When actual efficiency is used it is important to incorporate the auxiliary electrical energy used by the plant during normal operation. This is shown in Equation (3.4) [4] [55].

$$\eta_o = \frac{E_{gen} - E_{aux}}{E_{input}} \tag{3.4}$$

In Equation (3.4), η_o denotes the overall plant efficiency, E_{gen} denotes the electrical energy generated by the plant, E_{aux} denotes the auxiliary electrical energy consumed by the plant and E_{input} denotes the total energy content of fuel consumed by the plant. Evaluating overall plant efficiency in terms of component efficiencies is usually very difficult, as data must be measured and recorded for each of these subsystems, and obtained under carefully controlled test conditions [4]. However, some projects use Equation (3.5) to evaluate overall plant efficiency [4].

$$\eta_o = \eta_b * \eta_t * \eta_g * \eta_T \tag{3.5}$$

In Equation (3.5) η_o denotes the overall plant efficiency, η_b denotes the boiler efficiency, η_t denotes the turbine efficiency, η_g denotes the generator efficiency and η_T denotes the transformer efficiency [4]. This process does not account for any other inefficiencies in plant operation, and also does not consider the auxiliary electrical energy used in the plant.

Certain standards require heat and electrical efficiency to be calculated separately, in cases where waste heat energy is recuperated [4]. Thus a heat and electrical generation are calculated independently, as in Equations (3.6) to (3.7). The overall plant efficiency is thus calculated as in Equation (3.19) [4].

$$heat\ generation\ efficiency = \frac{heat\ energy\ output}{Total\ energy\ input} \tag{3.6}$$

$$power\ generation\ efficiency = \frac{electrical\ generation\ output}{total\ energy\ input} \tag{3.7}$$

$$\eta_o = \frac{heat\ energy\ output + electrical\ generation\ output}{total\ energy\ input} \tag{3.8}$$

3.3 Data envelopment analysis

3.3.1 Overview

In this section an introduction to the data envelopment analysis concept via definitions and examples is provided. The relevant efficiency concepts are discussed. A brief history of the process is provided. The mathematical basis of data envelopment is covered.

3.3.2 Introduction to data envelopment analysis

Data Envelopment Analysis (DEA) is a data-oriented, non-parametric benchmarking technique that utilises linear programming as its basis [57]. While still relatively new, DEA is a powerful process that is capable of comparatively evaluating numerous peer branches, or Decision Making Units (DMUs), making use of multiple numeric input and output categories [10] [14]. As these inputs and outputs can consist of any quantifiable values, DEA possibly includes almost any factor deemed relevant. The process identifies the most efficient DMUs, considering both the magnitude and ratio of inputs and outputs. Less efficient DMUs are compared to efficient DMUs. Inefficient DMUs are evaluated in their most efficient form i.e. the process attempts to make them appear as efficient as possible. The inefficient DMUs are also shown as ratios of efficient DMUs, utilising weighting factors. This information can be used to increase productivity in less efficient DMUs by helping them to follow practices utilised in more efficient DMUs [14]. DEA differs from a simple efficiency ratio in that it considers both *technical* and *scale* efficiency in its workings. Results take the form of *relative efficiency*. A 100% *relative efficiency* rating means that the DMU in question cannot be shown to be less efficient when compared to any other DMU [14].

DEA focuses on frontiers rather than central tendencies. This unique perspective means that the process can reveal relationships that conventional methodologies may not highlight [57] [14]. Variations and assumptions are kept to a minimum, resulting in a more accurate model. Also, the process can easily cope with a large number of DMUs. DEA has been adapted and used in various performance assessment applications, including hospitals, military wings, law firms, universities, banks, and, more recently, cases of electrical power generation and distribution [24], providing useful insights into the operating techniques in these activities, especially those that are difficult to analyse with conventional methods [14]. The process has also been proven to produce more accurate results than regression analysis methods [57].

Despite the above-mentioned advantages, there are a number of disadvantages to DEA's usage. DEA only provides a relative efficiency and does not provide an actual measure of efficiency [58] [10], which may prove troublesome, especially when used in an energy efficiency context. When evaluating non-homogenous units i.e. units completely different in nature, DEA will not produce meaningful results. The same can be said of similar units in non-homogenous environments [58]. Unit economics of scale also need to be carefully considered [58].

3.3.3 History of data envelopment analysis

A concept similar to that of DEA was proposed by M.J. Farrell in 1957 in his paper *The Measurement of Productive Efficiency*. Herein he attempted to develop a more effective model for measuring a productive efficiency. Farrell believed previous methodologies to be inadequate, as they could only include a single input category (usually labour) and ignored all other relevant categories [59]. His model was designed to be applicable to any process and he described the process as being applications “from a workshop to a whole economy” [14] [59].

The first true DEA model was developed by A. Charnes, W.W. Cooper and E. Rhodes in their 1978 paper entitled “*Measuring the efficiency of decision making units”* [60]. This was done after Rhodes unsuccessfully attempted to analyse data from U.S. Office of Education using traditional statistical-econometric methods [14]. Building on the work of M.J. Farrell, Charnes, Cooper and Rhodes developed a linear programming based methodology that would identify individual units on an efficient frontier [14]. Theirs is known as the *CCR* model and is the most basic form of DEA, with expanded models building on their basis.

3.3.4 DEA example

A simple example is utilised to illustrate the DEA process. This example is based on Example 2.4.1 in *Service Productivity Management: Improving Service Performance using Data Envelopment Analysis*, Sherman and Zhu, pages 57-62 [10]. Assuming five DMUs as in Table 3-2, all five DMUs produce the same output of category O_1. Each DMU has two input categories, namely I_1 and I_2.

Table 3-2: *DEA example.*

	Outputs	***Inputs***	
DMU	O_1	I_1	I_2
DMU_1	1000	20	300
DMU_2	1000	30	200
DMU_3	1000	40	100
DMU_4	1000	20	200
DMU_5	1000	10	400

From ***Table 3-2*** it can be seen that DMU_1 is inefficient when compared to DMU_4, as it uses 100 more units of category I_2 but produces the same output. Similarly, DMU_2 is inefficient when compared to DMU_4, using 10 more units of I_1 for the same output. Without additional information DMU_3, DMU_4 *and* DMU_5 cannot be seen to be more or less efficient in relation to each other. Applying DEA to the DMUs above produces the results in Table 3-3.

Table 3-3: *Results of DEA on Table 3-2.*

DMU	***Efficiency***	***Reference set***
DMU_1	85.7%	$\lambda_4 = 0.7143$, $\lambda_5 = 0.2857$
DMU_2	85.7%	$\lambda_3 = 0.2857$, $\lambda_4 = 0.7143$
DMU_3	100%	
DMU_4	100%	
DMU_5	100%	

Table 3-3 shows the same inefficient branches as determined by observation of ***Table 3-2***. The Lambda (λ) values under *Reference set* are the weights of the efficient DMUs which serve as references for the inefficient DMUs. Their values can be used to calculate the potential savings for the inefficient DMUs when the efficient DMUs are observed. Taking DMU_1 as example, the efficiency reference set compound DMU is calculated as in Equations (3.9) to (3.11).

DMU_4 weight and inputs	DMU_5 weight and inputs			
$\lambda_4 \times \begin{pmatrix} DMU_4\ I_1 \\ DMU_4\ I_2 \end{pmatrix}$	$+ \lambda_5 \times \begin{pmatrix} DMU_5\ I_1 \\ DMU_5\ I_2 \end{pmatrix}$	=	DMU'_1	(3.9)
$(0.7143) \times \begin{pmatrix} 20 \\ 200 \end{pmatrix}$	$+ \quad (0.2857) \times \begin{pmatrix} 10 \\ 400 \end{pmatrix}$	=	$\begin{pmatrix} 17.14 \\ 257.14 \end{pmatrix}$	(3.10)

In the above equations DMU'_1 refers to DMU_1's projections onto the efficient frontier as the new efficient compound DMU. It should be noted that the output remains unchanged. Comparing the results of the above calculation to the actual input values of DMU_1, we find the excess inputs used (and thus potential savings) as in Equation (3.11) to (3.12).

DMU_1 weight and inputs		DMU'_1 weight and inputs		Potential savings.	
					(3.11)
$\begin{pmatrix} 20 \\ 300 \end{pmatrix}$	$-$	$\begin{pmatrix} 17.14 \\ 257.14 \end{pmatrix}$	=	$\begin{pmatrix} 2.86 \\ 42.86 \end{pmatrix}$	(3.12)

Thus, when using DMU_4 and DMU_5 as reference, DMU_1 can produce the same output but potentially use 2.86 units less of I_1 and 42.86 units less of I_2.

DMU_3, DMU_4 and DMU_5 can thus be seen to be the efficient frontier whereby the value of inefficient branches is calculated, as with DMU_1 above. This is demonstrated graphically in Figure 3-1 [10].

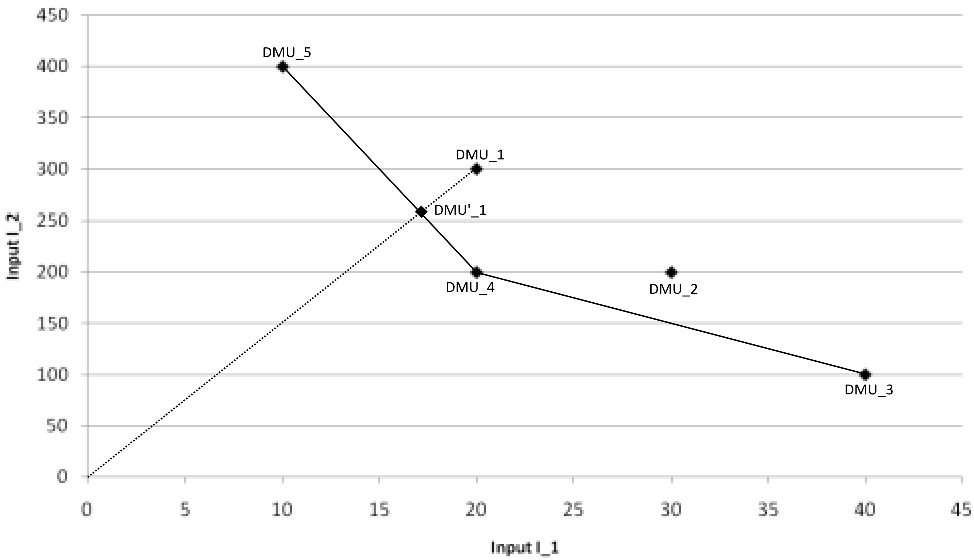


***Figure 3-1**: Graphical representation of DEA example [10].*

3.3.5 The Charnes, Cooper and Rhodes model

3.3.5.1 Overview of CCR model

As stated in section 3.3.3, the Charnes, Cooper and Rhodes (*CCR*) model (also called the *primal* or *multiplier* model) forms the basis of almost all DEA methods. It is explained below.

Efficiency is commonly calculated as in Equation (3.13), which can be seen to be identical to Equation (3.1), except the symbol θ is now used to represent total efficiency.

$$\theta = \frac{\Sigma\ output}{\Sigma\ input} \tag{3.13}$$

Thus, a higher efficiency is achieved but increasing the output and/or decreasing the input. However, complex systems may have more than one input or output category that cannot be evaluated additively. DEA's strength lies in its ability to accommodate multiple inputs and outputs and accommodate their unique value systems [55]. By associating weights with each IO category, the DEA process manipulates the relative contributions of the individual input and output parameters on the efficiency metric θ. Weights also allow each DMU to become more efficient in the most suitable manner [10].

When evaluating the o^{th} DMU of a total number of j DMUs, efficiency can be calculated using the relationship shown in Equation (3.14).

$$\theta = \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{io}} \tag{3.14}$$

In Equation (3.14) x_{io} denotes i^{th} input value of the oth DMU, y_{ro} denotes the r^{th} output value the oth DMU, u_r denotes the weight of output parameter y_{ro}, v_i denotes the weight of input x_{io}, and m and s denote the number of input and output parameters respectively. Equation (3.14) serves as the objective function, but is subject to the constraint that the u and v values for a specific DMU will not produce a value that is greater than 1, as in Equation (3.15).

$$\begin{gathered} DMU_1 \frac{u_1 y_{11} + u_2 y_{21} + \cdots + u_r y_{r1}}{v_1 x_{11} + v_2 x_{21} + \cdots + v_m x_{m1}} = \frac{\sum_{r=1}^{s} u_r y_{r1}}{\sum_{i=1}^{m} v_i x_{i1}} \leq 1 \\ DMU_2 \frac{u_1 y_{12} + u_2 y_{22} + \cdots + u_r y_{r2}}{v_1 x_{12} + v_2 x_{22} + \cdots + v_m x_{m2}} = \frac{\sum_{r=1}^{s} u_r y_{r2}}{\sum_{i=1}^{m} v_i x_{i2}} \leq 1 \\ \cdots \\ DMU_j \frac{u_1 y_{1j} + u_2 y_{2j} + \cdots + u_r y_{rj}}{v_1 x_{1j} + v_2 x_{2j} + \cdots + v_m x_{mj}} = \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1 \end{gathered} \tag{3.15}$$

$$u_r \ \geq 0, with\ r = 1,2, \dots, s \tag{3.16}$$

$$v_i \ \geq 0, with\ i = 1,2, \dots, m \tag{3.17}$$

To solve Equation (3.15) to (3.17) using linear programming, they are rearranged as follows:

$$Maximize\ \theta = \sum_{r=1}^{s} u_r y_{ro} \tag{3.18}$$

$$\sum_{i=1}^{m} v_i x_{io} = 1 \tag{3.19}$$

$$u_1 y_{1j} + u_2 y_{2j} + \cdots + u_r y_{rj} \leq v_1 x_{1j} + v_2 x_{2j} + \cdots + v_m x_{mj} \tag{3.20}$$

Equations (3.18) to (3.20) represent the original form of the CCR model [57] [60]. In order to solve the constrained optimisation problem by conventional linear programming methods, Equation (3.20) is written in standard mathematical notation as in Equation (3.21) [10]:

$$\sum_{r=1}^{s} u_r y_{rj} \leq \sum_{i=1}^{m} v_i x_{ij} \tag{3.21}$$

This gives rise to a simplified objective function given by Equation (3.18) and constraints given by Equations (3.22) to (3.25).

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_{ij} \leq 0\ , j = 1,2 \ldots n \tag{3.22}$$

$$\sum_{i=1}^{m} v_i x_{io} = 1 \tag{3.23}$$

$$u_r \geq 0, with\ r = 1,2, \ldots , s \tag{3.24}$$

$$v_i \geq 0, with\ i = 1,2, \ldots , m \tag{3.25}$$

The mathematical model represented Equations (3.22) to (3.25).is known as the primal model. It treats the rows of the linear programming problem as the model and seeks to maximize the output defined by Equation 3.1.6. It should be noted that in Equation 3.1.10 to Equation 3.1.13 the *u* and *v* weight variables are defined as non-negative. However, for a more accurate model, they should be described as greater than *ε*, which represents an infinitesimally small non-zero positive value, as is shown in Equation (3.26) [14].

$$u_r, v_i \geq \varepsilon > 0, with\ i = 1,2, \ldots , m \tag{3.26}$$

3.3.5.2 Output orientation versus input orientation

The CCR model as formulated in 0 is said to be in its *input-orientated* form. This means that DEA attempts to reduce the inputs but maintain the same output. A second form, known as *output-orientated* form, is formulated in Equation (3.27) to (3.31) [10]. When DEA is applied to this form it attempts to keep inputs constant but maximize the output.

$$minimize\ \theta = \sum_{i=1}^{m} v_i x_{io} \tag{3.27}$$

subject to

$$\sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} u_r y_{rj} \geq 0 \quad j = 1, \dots, n \tag{3.28}$$

$$\sum_{r=1}^{s} u_r y_{ro} = 1 \tag{3.29}$$

$$u_r > 0, with\ r = 1,2, \dots, s \tag{3.30}$$

$$v_i > 0, with\ i = 1,2, \dots, m \tag{3.31}$$

The results of the output orientated DEA can be said to be "inverted" i.e. a value of 1 still indicates an efficient DMU, however a value of *greater* than 1 indicates an inefficient DMU [10]. If an output orientated DEA is applied to the example in section 3.3.4 the results in ***Table 3-4*** are produced.

Table 3-4*: Output orientated DEA example.*

DMU	*Efficiency*
DMU_1	116.69%
DMU_2	116.69%
DMU_3	100%
DMU_4	100%
DMU_5	100%

Examining ***Table 3-4***, *DMU_1* and *DMU_2* are once again seen to be inefficient. Taking their inverse around 100% produces the same result as that shown in ***Table 3-2***. The results of both the input and output orientated DEA are compared in ***Figure 3-2***. It can be seen that the two result sets are symmetrical about 100% efficiency as a result of being symmetrical inversions of one another around the 100% axis.

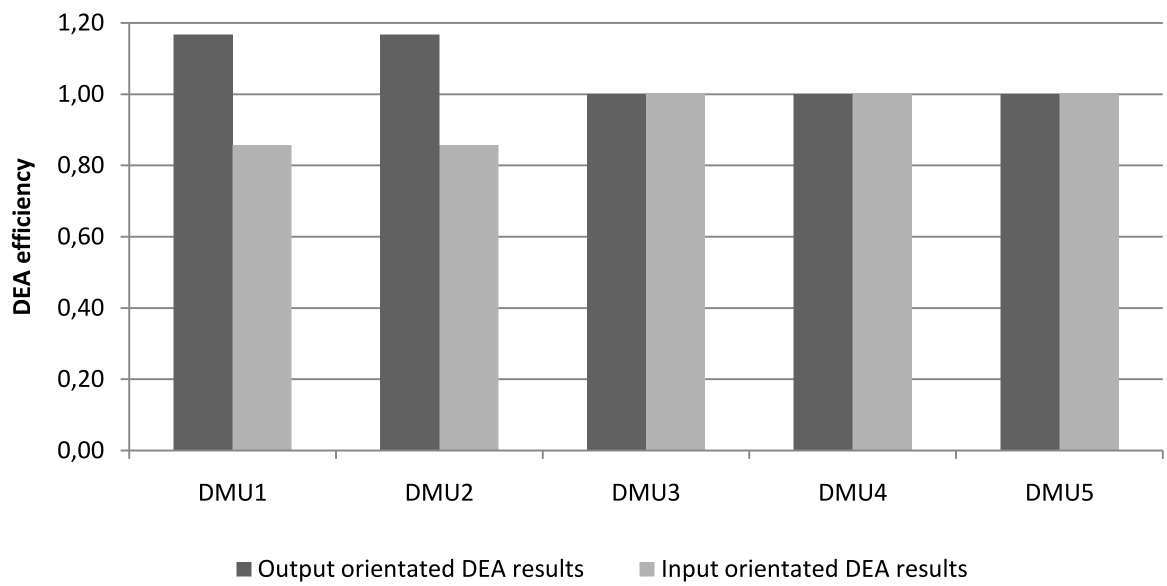


***Figure 3-2**: Input and output orientated DEA results.*

3.3.6 The envelopment model

The model formulated in section 3.3.5 is often resource-intensive and difficult for a standard linear programming package to solve. The *v* and *u* values from the CCR model are associated with each input and output category respectively. However, it may be desired to have weights associated with each DMU instead. Both the above problems are addressed by the *envelopment model* or *dual model.* The process is also sometimes called the Farrell model, because of its resemblance to Ferrell's original formulation of 1957 [14]. However, to formulate this form it is first necessary to understand the concept of the linear programming dual form. This is explained in section 3.3.6.2.

3.3.6.1 Linear programming dual form

A linear program is defined as an optimisation process which maximizes or minimizes a predetermined objective function. The basic form of a linear program is called its *primal*. Each linear program has a second associated problem know as its *dual*. If the primal is a maximisation process, the dual will be a minimisation process, and vice-versa [61]. The optimised values of the primal and dual forms will always be equal. The dual will have a single variable for each of the constraints in the primal form, which can be viewed as the "cost" of each constraint [61].

3.3.6.2 Formulation of dual form

Assuming a primal form of a linear programming problem as in Equations (3.32) to (3.34) [61]:

$$\boldsymbol{objective\ function}: minimise\ or\ maximise: \ [c_1\ c_2\ \cdots c_n]\begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} = \boldsymbol{c^T}\mathbf{x} \tag{3.32}$$

$$subject\ to: \begin{bmatrix} A_{11}\ A_{12}\ \cdots A_{1m} \\ A_{21}\ A_{22}\ \cdots A_{2m} \\ \vdots \\ A_{n1}\ A_{n2}\ \cdots A_{nm} \end{bmatrix}\begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} = \boldsymbol{Ax} \geq \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_n \end{bmatrix} = \boldsymbol{b} \tag{3.33}$$

$$and\ \boldsymbol{x} \geq 0 \tag{3.34}$$

In Equations (3.32) to (3.34) x_i denotes i^{th} variable in the LP, c_n denotes the coefficient of the n^{th} LP variable in the objective function and is known as the cost vector, A_{nm} denotes the coefficient matrix of the LP variables on the LHS of each constraint, and b_n denotes the RHS constant of the n^{th} constraint and is called the constraint vector. To obtain the dual form of the primal in Equations (3.32) to (3.34), a new variable is defined per constraint. Therefore there will be *m* new variables, labelled λ_1 to λ_m. The dual can be thought of as the "negative transpose" of the primal. Therefore the coefficient matrix $\boldsymbol{A}$ is transposed, the cost and solution vectors ($\boldsymbol{c^T}$ and $\boldsymbol{b}$ respectively) and inequalities as well as the objective function are reversed [61]. This produces the dual model shown by Equations (3.35) to (3.37) [61].

$$\boldsymbol{objective\ function}: maximise\ or\ minimise:\ [\lambda_1\ \lambda_2\ \cdots \lambda_n] \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_n \end{bmatrix} = \boldsymbol{\lambda}^T \mathbf{b} \tag{3.35}$$

$$subject\ to: [\lambda_1\ \lambda_2\ \cdots \lambda_n] \begin{bmatrix} A_{11}\ A_{12}\ \cdots A_{1m} \\ A_{21}\ A_{22}\ \cdots A_{2m} \\ \vdots \\ A_{n1}\ A_{n2}\ \cdots A_{nm} \end{bmatrix} = \boldsymbol{\lambda}^T \mathbf{A} \leq [\boldsymbol{c_1}\ \boldsymbol{c_2}\ \cdots \boldsymbol{c_n}] = \boldsymbol{c}^T \tag{3.36}$$

$$and\ \boldsymbol{\lambda}^T \geq 0 \tag{3.37}$$

3.3.6.3 Formulation of the envelopment model

Applying the dual linear programming model to Equation 3.1.9 to 3.1.13 produces the new model below in Equation (3.38) to (3.39) [57].

$$\sum_{k=1}^{s} \lambda_j x_{ij} \leq \theta x_o \tag{3.38}$$

$$\sum_{k=1}^{n} \lambda_j y_{rj} \geq y_{ro} \tag{3.39}$$

$$\lambda_j \geq 0 \tag{3.40}$$

In Equations (3.38) to (3.39) the λ values are the variables added by the dual process. From a computational perspective, the dual model is simpler compared to the primal model [55]. Since the input is being minimized, the resulting λ values can be interpreted as a hypothetical compound DMU, showing what percentages of relatively efficient DMUs inputs can be used by an inefficient DMU to produce the same output [55]. This data can be used to calculate the potential savings associated with more efficient DMUs [10]. It should be noted that the above model has constant returns-to-scale in its standard form. This is expanded on in section 3.3.6.4.

3.3.6.4 Variations on return-to-scale in envelopment model

Return-to-scale (RTS) is a term used in economics when describing the effect of scaling on the relationship between inputs and outputs. In the context of DEA, RTS can be used as a means of identifying inefficiencies that may be caused by DMU scale [10]. The constant RTS of the standard envelopment model means that scale effects are “filtered” out. RTS is demonstrated simply in the following example. Assuming a DMU produces output *y* with input *x.* If *x* is doubled its potential RTS definitions are explained in ***Table 3-5***.

Table 3-5*: Return to scale definitions.*

Output	*Return to scale*

Output	*Return to scale*
= 2y	Constant (CRS)
< 2y	Decreasing (DRS)
> 2y	Increasing (IRS)

RTS is demonstrated visually in ***Figure 3-3*** [10]. The line 0A represents the efficient frontier for a constant RTS orientation. Thus only DMU_2 and DMU_3 would be deemed efficient. However, a non-increasing RTS frontier is represented by the segments 0DEF. Now DMU_2 , DMU_3, DMU_4 and DMU_5 are all considered efficient. Similarly, a non-decreasing RTS frontier is represented by the segments BCDA. DMU_1, DMU_2 and DMU_3 are now considered efficient [10]. If a variable RTS is employed, the line BCDEF becomes the efficient frontier, making DMU_1, DMU_2 , DMU_3, DMU_4 and DMU_5 efficient.

When different RTS orientations are used non-efficient DMU's may vary in value. Consider DMU_6 in ***Figure 3-3***. When a non-increasing RTS is employed, DMU_6' becomes the efficient target for DMU_6. When a non-decreasing RTS is employed DMU_6 gains the new efficient target DMU_6'' [10].

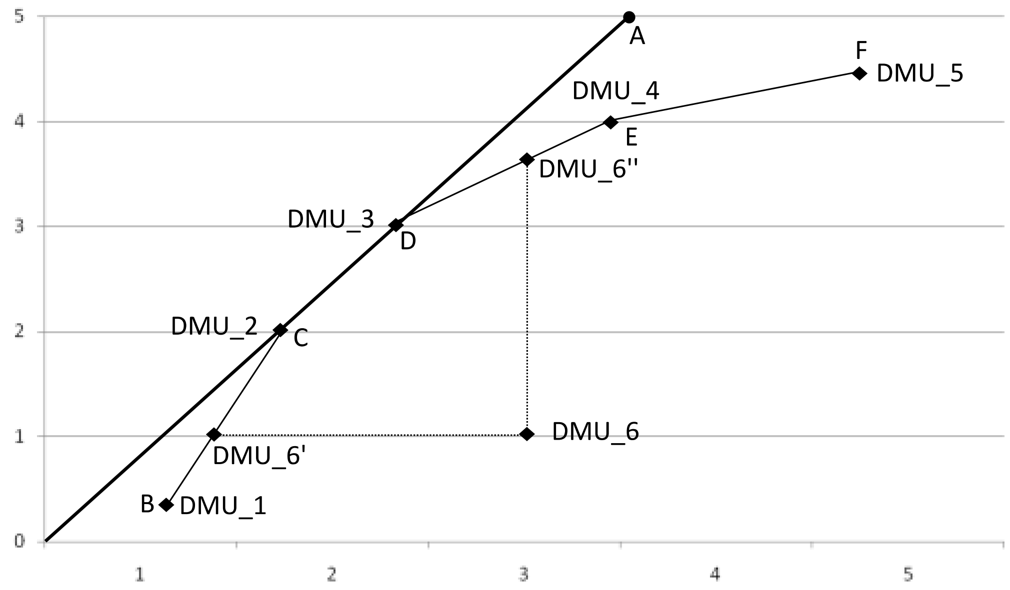


Figure 3-3*: Non-increasing and non-decreasing RTS.*

The RTS of the envelopment DEA model is determined by adding an additional constraint as in Equation (3.41).

$$\sum_{j=1}^{s} \lambda_j \tag{3.41}$$

Usually this term is unbounded (resulting in a constant RTS) [10], but by applying the following constraints the RTS can be affected as in ***Table 3-6***.

***Table 3-6**: RTS constraints to envelopment model [10].*

Constraint to envelopment model	*Return to scale*
$\sum_{j=1}^{s} \lambda_j = 1$	Variable[2]
$\sum_{j=1}^{s} \lambda_j \leq 1$	Non-increasing
$\sum_{j=1}^{s} \lambda_j \geq 1$	Non-decreasing

[2] The envelopment model with this constraint included is sometimes referred to as the *Banker, Charnes and Cooper (BCC)* model [14].

4 Database and application development

4.1 Overview of database and application development

In this chapter the design and implementation of both a relational database and software application are covered. These are summarised below:

- *Development and implementation of relational database:* The development of a relational database is covered in detail. This includes the *project, plant and unit* and *profileset, profile and profiledata* subsections. The various database tables are shown with relevant attributes, as well as a description of each attribute's type and purpose. Table hierarchies are shown, as well as a complete database structure. The database testing procedure is also included.
- *Development and implementation of software application:* The development of a software application is described with the emphasis on software engineering approaches, including the unified modelling language and the unified process principles. The functional requirements of the application are described as well as the system architecture. The development of each module is described in terms of its requirements. Use-case and activity diagrams are shown for each module and for the complete application. Finally, the software testing process is described.

4.2 Database development

4.2.1 Overview of database development

In this section the database design and implementation process followed in this project are described. This relational database is used for the storage of plant information, including historical input and output data and plant specifications. As the database must store data for numerous projects, plants and units, a versatile generic design is employed. For the testing process the database is implemented on *WAMPserver 2.2*. The database is covered in 3 sections, namely *Database structure for projects, Database structure for plant and unit* and *Database structure for profile sets, profiles* and profile data, in sections 4.2.2, 4.2.3 and 4.2.4 respectively.

4.2.2 Database structure for projects

It is necessary for the database to incorporate multiple separate projects. Each plant is thus designated to a specific project, making a *project* table necessary. This table is shown in ***Figure 4-1***.

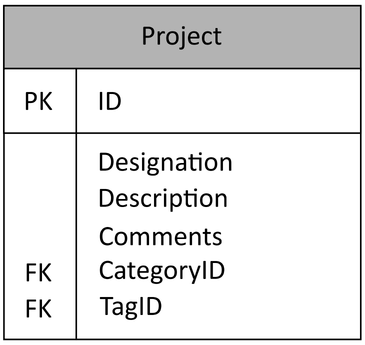


***Figure 4-1**: Design of project table.*

The *project* table includes the *ID* attribute, used as the primary key (PK). The *designation* attribute is used to store a brief description of any entries, while the *description* attribute stores entry names. *Comments* allows for the storage of any additional relevant entry information. To allow for the storage of additional project information, *category* and *tag* tables are added. The *category* table allows for easy categorisation of projects, while the *tag* table allows project designation as active or inactive. The *CategoryID* and *TagID* attributes in ***Figure 4-1*** are foreign keys (FK) that point to the *Category* and *Tag* tables respectively, as shown in ***Figure 4-2***, along with the FK relations to the *project* table.

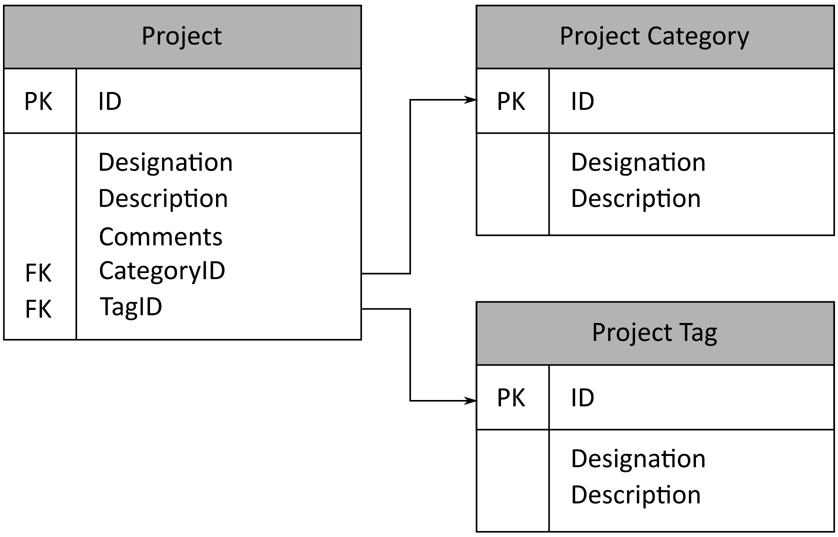


***Figure 4-2**: Design of project, project category and project tag tables.*

The *project category* and *project tag* tables both include the *designation* and *description* attributes, used as in the *project* table. These are used to store a brief explanation of the project category or project tag and the name of the project category or project tag respectively. The *ID* attribute serves as the unique PK for each table. The complete attributes of the *project* table and its FK tables are shown in ***Table 4-1***.

***Table 4-1**: Attributes of project, project category and project tag tables.*

Table	**Attribute**	**Description**
Project	ID	Unique numeric primary key of project.
	Designation	Brief explanation of the nature of project.
	Description	Name of project.
	Comments	Contains any additional relevant information.
	CategoryID	Foreign key pointing from *project* table to *project category* table.
	TagID	Foreign key pointing from *project* table to *project tag* table.
Project Category	ID	Unique numeric primary key of project category.
	Designation	Brief explanation of the nature of project category.
	Description	Name of project category.
Project Tag	ID	Unique numeric primary key of project tag.
	Designation	Brief explanation of the nature of project tag.
	Description	Name of project tag.

4.2.3 Database structure for plant and unit

This database is created to store historical plant data. As such, it is imperative that the database be arranged around a table containing a list of plants and their metadata. For this the *plant* table is created, as shown in ***Figure 4-3***.

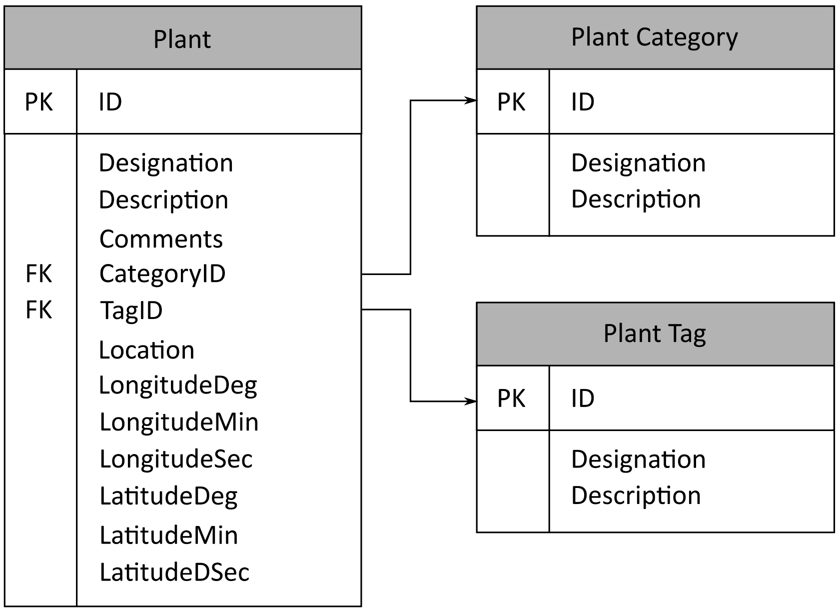


***Figure 4-3**: Design of plant, plant category and plant tag tables.*

As with the *project* table, the *plant* table includes *designation, description, comments, categoryID* and *tagID* attributes, which are used as before. The *categoryID* and *tagID* FKs point to the *plant category* and *plant tag* tables respectively. The *plant category* allows for the easy classification of the plant. This typically consists of the plant technology e.g. coal-fired, solar. The *plant tag* table allows for the differentiating of active and inactive states of the plant. Both these tables include the *designation* and *description* attributes, used as before.

The *plant* table is linked to the *project* table via a link table. This allows for easy versatility and re-usability of the database if repurposed for use in a non-plant role. The *link project plant* table is used as the link table in this case and is shown in ***Figure 4-4***. The *project* and *plant* tables are also shown to illustrate link table usage.

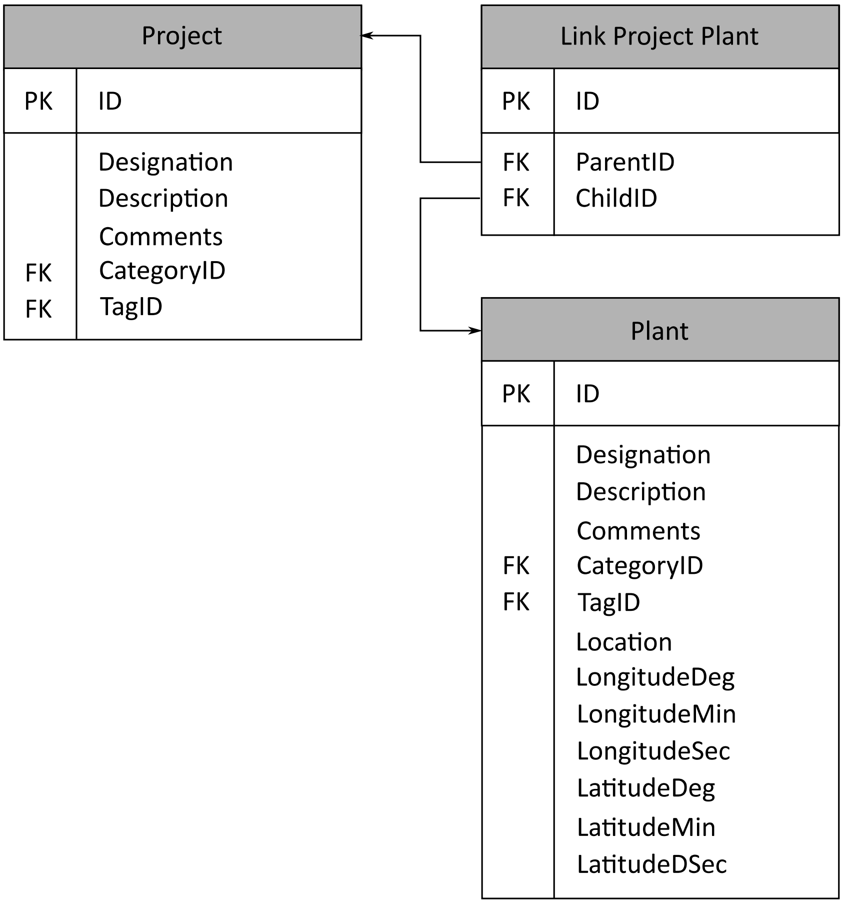


Figure 4-4*: Design of plant, link project plant and project tables.*

The *link project plant* table includes an *ID* PK as before. However, two FKs are made use of to associate the *plant* and *project* tables, namely *parentID* and *childID*. *ParentID* points to the relevant project while *childID* points to the relevant plant. A project can thus have multiple associated plants if required. The attributes used in *plant, plant category, plant tag* and *link project plant* are shown in ***Table 4-2***

Table 4-2*: Attributes of plant, plant category, plant tag and link project plant tables.*

Table	**Attribute**	**Description**
Plant	ID	Unique numeric primary key of plant.
	Designation	Brief explanation of the nature of plant.

Table	Attribute	Description
	Description	Name of plant.
	Comments	Contains any additional relevant information.
	CategoryID	Foreign key pointing from *plant* table to *plant category* table.
	TagID	Foreign key pointing from *plant* table to *plant tag* table.
	LongitudeDeg	Geographical plant location degrees of longitude.
	LongitudeMin	Geographical plant location minutes of longitude.
	LongitudeSec	Geographical plant location seconds of longitude.
	LatitudeDeg	Geographical plant location degrees of latitude.
	LatitudeMin	Geographical plant location minutes of latitude.
	LatitudeSec	Geographical plant location seconds of latitude.
Plant Category	ID	Unique numeric primary key of plant category.
	Designation	Brief explanation of the nature of plant category.
	Description	Name of plant category.
Plant Tag	ID	Unique numeric primary key of plant tag.
	Designation	Brief explanation of the nature of plant tag.
	Description	Name of plant tag.
Link Project Plant	ID	Unique numeric primary key of link project plant.
	ParentID	Foreign key pointing to relevant project in *project* table.
	ChildID	Foreign key pointing to relevant plant in *plant* table.

As it is necessary to include the individual units of a plant in an analysis, a *unit* table is included. To allow for classification of plant units, a *unit category* table is added, as well as a *unit tag* table to allow for distinguishing between active and inactive units. A link table *link unit* is used to associate units with plants in the *plant* table. The *unit, unit category, unit tag, link unit* and *plant* tables are shown in ***Figure 4-5***.

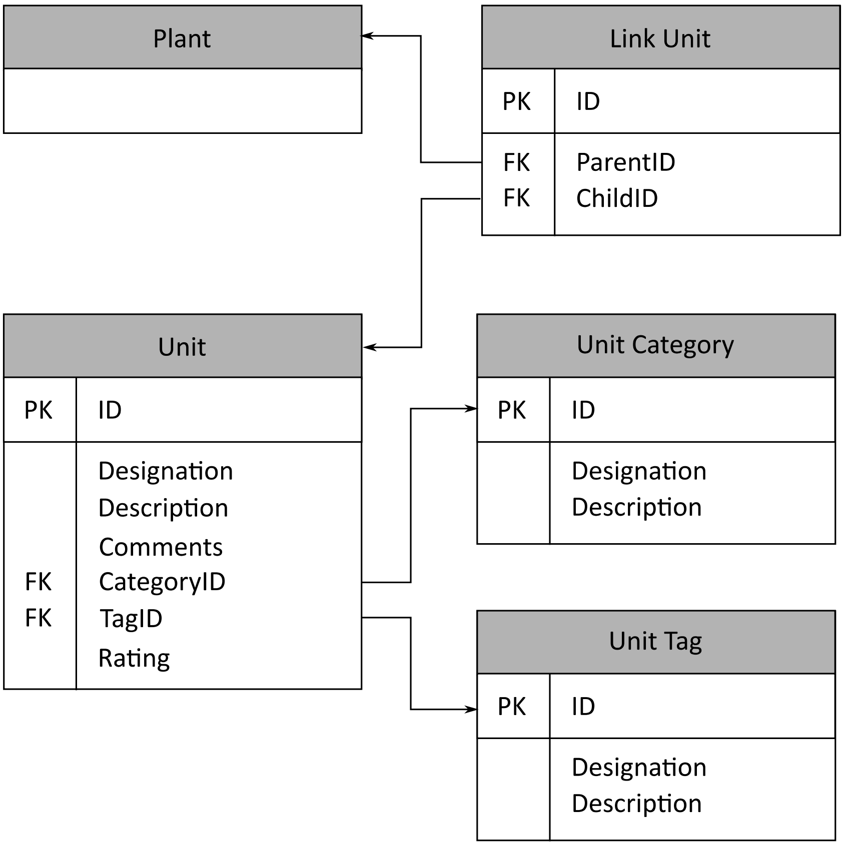


Figure 4-5*: Design of plant, link unit, unit, unit category and unit tag tables.*

The *unit* table includes *ID, designation, description, categoryID* and *tagID* attributes as before. The *rating* attribute hold the MW rating of the unit. The attributes for *unit, linkunit, unit category* and *unit tag* are shown in ***Table 4-3***.

Table 4-3*: Attributes of unit, unit category, unit tag and link unit tables.*

Table	**Attribute**	**Description**
Unit	ID	Unique numeric primary key of unit.
	Designation	Brief explanation of the nature of unit.
	Description	Name of unit.
	Comments	Contains any additional relevant information.
	CategoryID	Foreign key pointing from *unit* table to *unit category* table.
	TagID	Foreign key pointing from *unit* table to *unit tag* table.
	Rating	MW rating of unit.
Unit Category	ID	Unique numeric primary key of unit category.
	Designation	Brief explanation of the nature of unit category.
	Description	Name of unit category.
Unit Tag	ID	Unique numeric primary key of unit tag.
	Designation	Brief explanation of the nature of unit tag.
	Description	Name of unit tag.
Link Unit	ID	Unique numeric primary key of link unit.
	ParentID	Foreign key pointing to relevant plant in *plant* table.
	ChildID	Foreign key pointing to relevant unit in *unit* table.

4.2.4 Database structure for profile sets, profiles and profile data

It is preferable for the data to be arranged in profiles. These profiles are in turn arranged by profile sets, thus prompting a *profile set* table. Each profile set is associated with a plant unit, so a link table, namely *link unit profileset*, is again used to link *profileset* to *unit* table. The use of the link table means that the profile-based database can be repurposed for use in a non-plant related context without many alterations. The *profileset* table includes the *ID* PK again, as well as the *designation, description* and *comment* attributes. FKs *categoryID* and *tagID* are included to point to tables *profileset category* and *profileset tag* respectively.

As mentioned above, data is arranged by profiles, so a *profile* table is included. Each profile is associated with a particular profile set, so a link table is again used, namely *link profile*. The *profile* table has PK *ID*. Two FK attributes are included, *categoryID* and *tagID*, which point to tables *profile category* and *profile tag* respectively, which are used as before. The *profile* table also includes the *unitID* attribute, a FK which points to an additional table *profile unit*. The *profile unit* table is used to record the unit of measurement associated with a certain profile, and should not be confused with the *unit* table mentioned above. The *linkunitprofileset, profileset, profileset category, profileset tag, link profile, profile, profile category, profile tag* and *profile unit* tables are shown in ***Figure 4-6***.

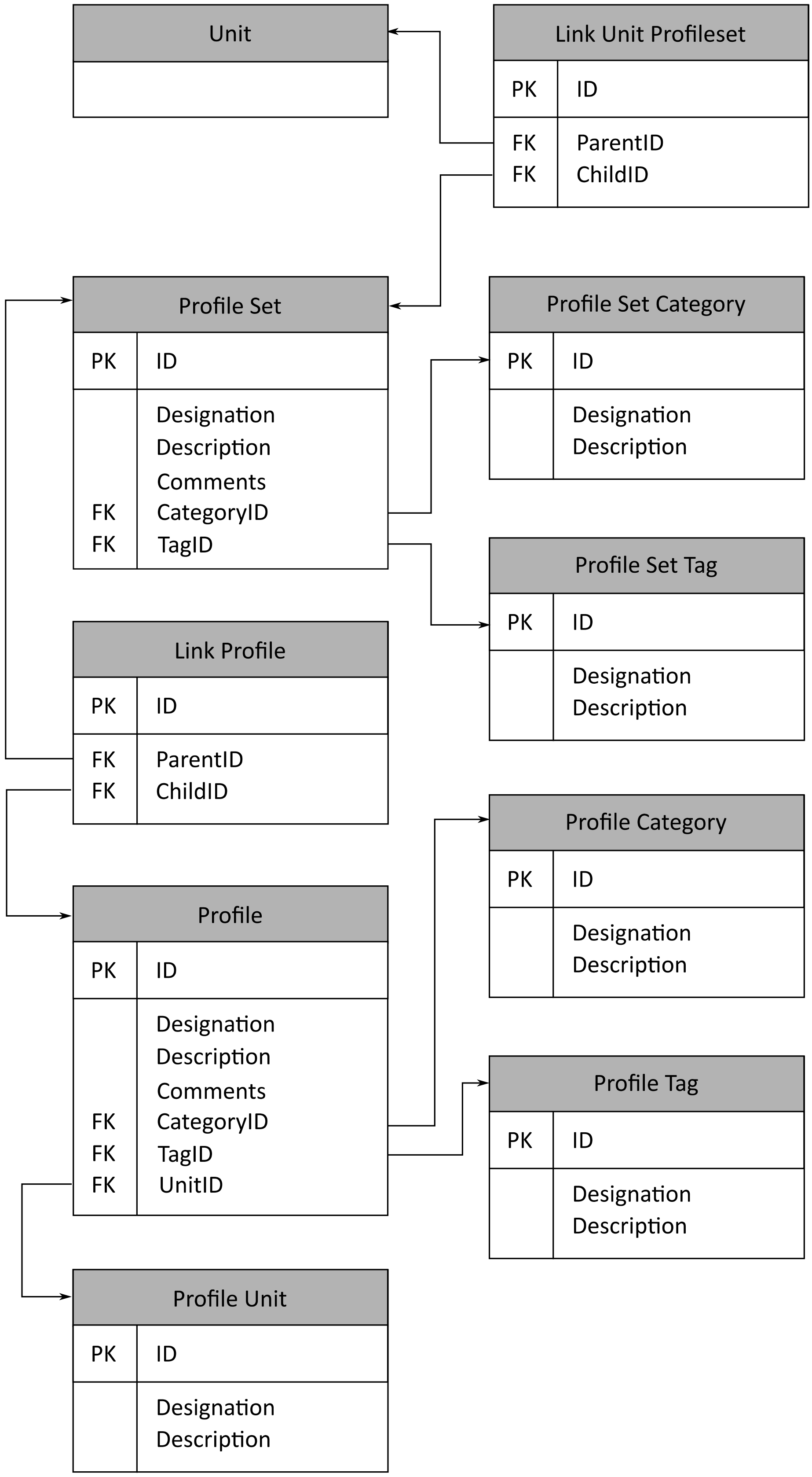


***Figure 4-6**: Design of linkunitprofileset, profileset, profileset category, profileset tag, link profile, profile, profile category, profile tag, profile unit tables.*

The attributes used in the *linkunitprofileset, profileset, profileset category, profileset tag, link profile, profile, profile category, profile tag* and *profile unit* tables are shown in ***Table 4-4***.

Table 4-4*: linkunitprofileset, profileset, profileset category, profileset tag, link profile, profile, profile category, profile tag, profile unit tables.*

Table	**Attribute**	**Description**
Profile Set	ID	Unique numeric primary key of profile set.
	Designation	Brief explanation of the nature of profile set.
	Description	Name of profile set.
	Comments	Contains any additional relevant information.
	CategoryID	Foreign key pointing from *profile set* table to *profile set category* table.
	TagID	Foreign key pointing from *profile set* table to *profile set tag* table.
Profile Set Category	ID	Unique numeric primary key of profile set category.
	Designation	Brief explanation of the nature of profile set category.
	Description	Name of profile set category.
Profile Set Tag	ID	Unique numeric primary key of profile set tag.
	Designation	Brief explanation of the nature of profile set tag.
	Description	Name of profile set tag.
Link Unit Profile Set	ID	Unique numeric primary key of *link unit profile set*.
	ParentID	Foreign key pointing to relevant unit in *unit* table.
	ChildID	Foreign key pointing to relevant profileset in *profileset* table.
Profile	ID	Unique numeric primary key of profile.
	Designation	Brief explanation of the nature of profile.
	Description	Name of profile.
	Comments	Contains any additional relevant information.
	CategoryID	Foreign key pointing from *profile* table to *profile category* table.
	TagID	Foreign key pointing from *profile* table to *profile tag* table.
Profile Category	ID	Unique numeric primary key of profile category.
	Designation	Brief explanation of the nature of profile category.
	Description	Name of profile category.
Profile Tag	ID	Unique numeric primary key of profile tag.
	Designation	Brief explanation of the nature of profile tag.
	Description	Name of profile set tag.
Profile Unit	ID	Unique numeric primary key of profile unit.
	Designation	Brief explanation of the nature of profile unit.
	Description	Name of profile set unit.
Link Profile	ID	Unique numeric primary key of *link profile*.
	ParentID	Foreign key pointing to relevant profile set in *profile set* table.
	ChildID	Foreign key pointing to relevant profile in *profile* table.

For the storage of historical plant data a table *profile data* is used. *Profile data* again uses an *ID* attribute as its PK. A *value* attribute is used to store the historical data for each entry. A *tag ID* attribute is added as a FK which points to a table *profile data tag.* An additional table is added to hold profile data timestamp values, namely *profile timestamp*. An FK attribute *timestampID* is added to the *profile data* table to point to specific entries in the *timestampID* table, thus associating each historical data entry with the relevant timestamp. The *profile timestamp* table includes a *timestamp* attribute. A link table *link profile data* is used to associate each *profile data* entry with the relevant entry in the *profile* table. The *profile data, profile data tag, profile timestamp* and *link profile data* tables are show in ***Figure 4-7***.

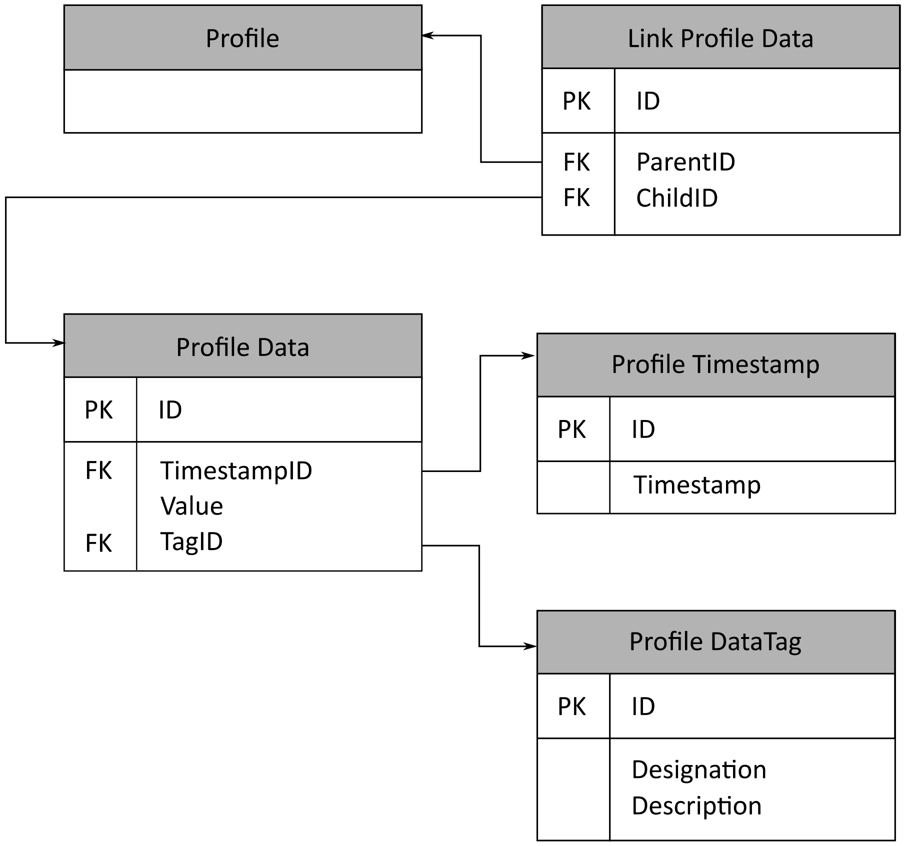


Figure 4-7*: Design of profile data, link profile data, profile timestamp and profile data tag tables.*

The attributes used in the *profile data, profile data tag, profile timestamp* and *link profile data* tables are shown in ***Table 4-5***.

Table 4-5*: Attributes of profile data, profile data tag, profile timestamp and link profile data tables.*

Table	**Attribute**	**Description**
Profile Data	ID	Unique numeric primary key of profile data.
	TimestampID	Foreign key pointing from *profile data* to *profile timestamp* table.
	Value	Numeric value of profile data entry.
	TagID	Foreign key pointing from *profile data* table to *profile data tag* table.
Profile Timestamp	ID	Unique numeric primary key of unit category.
	Timestamp	Timestamp value of entry.
Profile Data Tag	ID	Unique numeric primary key of profile data tag.
	Designation	Brief explanation of the nature of profile data tag.
	Description	Name of profile data tag.
Link Profile Data	ID	Unique numeric primary key of link unit.

Table	Attribute	Description
	ParentID	Foreign key pointing to relevant profile in *profile* table.
	ChildID	Foreign key pointing to relevant profile data entry in *profile data* table.

The complete database is shown in ***Figure 4-8***.

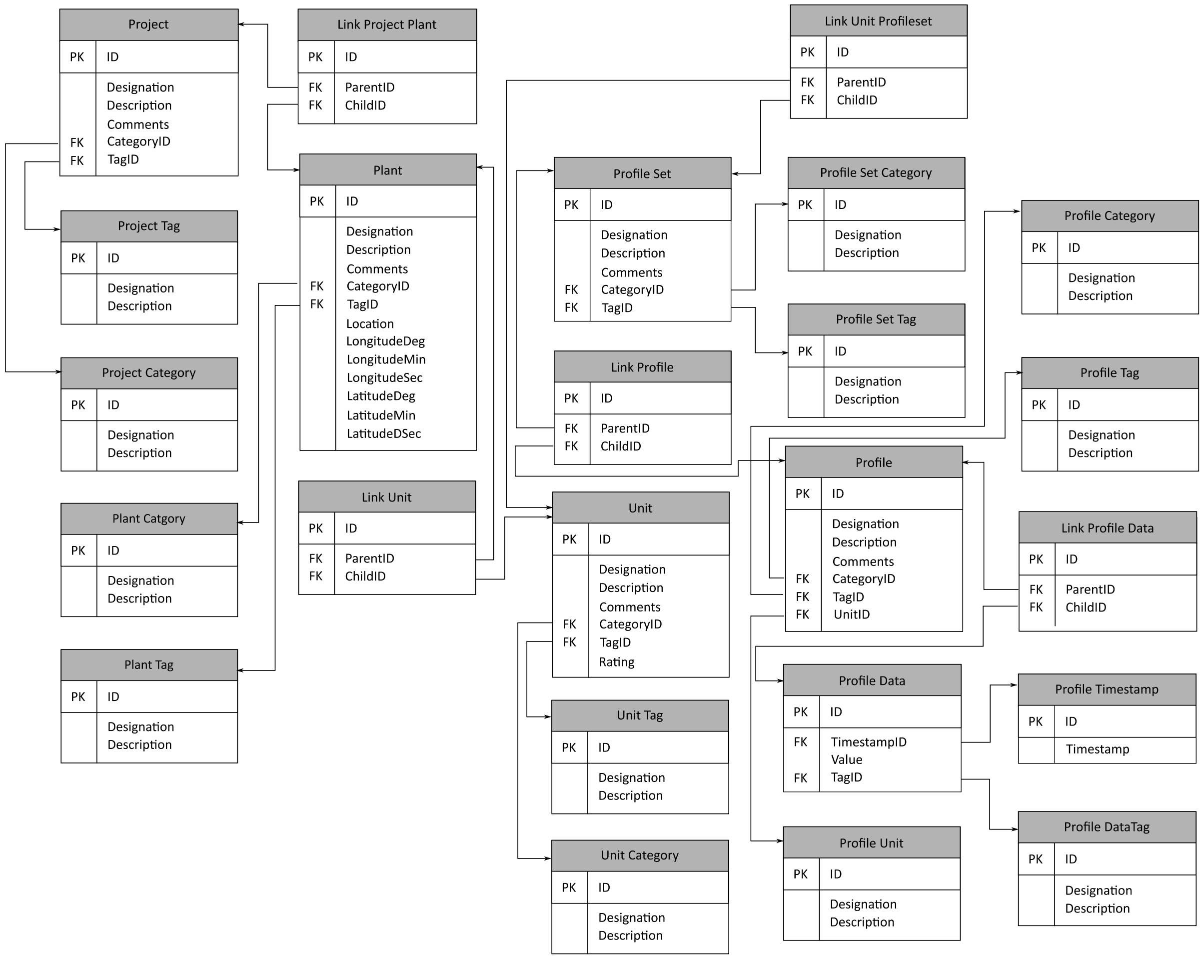


***Figure 4-8**: Design of complete relational database.*

4.2.5 Database implementation and testing

The database design was implemented using *MySQL Query Browser* for Microsoft® Windows™ on the *MySQL* database platform. The *Innodatabase* table engine is utilised, as this is the most widely used example and incorporates FK support. For testing, historical plant data is stored on the database and arranged by project, plant, unit and profiles. The database is implemented on *WAMPserver*, as this offers excellent *MySQL* support, on Microsoft® Windows™. To test the database, *MySQL Query Browser* is employed to query the database using SQL queries. It can thus be confirmed whether the database is working correctly and has been correctly structured.

4.3 Application development

4.3.1 Overview of application development

In this section the development of a software application that is capable of tracking plant efficiency using classical methods and Data Envelopment Analysis (DEA) is described. This application incorporates historical plant generation and environmental data and makes use of a relational database. The software development was done while observing the development strategies and disciplines of the Unified Process (UP) . The four UP disciplines that are used to guide the design and implementation of the software are [41]:

- Inception phase.
- Elaboration phase.
- Construction phase.
- Transition phase.

The system design is shown in terms of the use the Unified Modelling Language (UML) case diagrams and activity diagrams.

4.3.2 Inception phase

In this phase the scope and feasibility of the project are defined. The phase outputs consist of the final vision, an initial use case model, major project risks and a transitional system architecture.

4.3.2.1 Software application scope and requirements

The eventual goal of this design is the implementation of a Windows™-based software application that utilises historical data stored on a separate relational database to track efficiency over time and comparatively between plants for Measurement and Verification (M&V) applications. The following are requirements for the final iteration of the application:

- Connect to database of user's choice.
- Access historical data on database.
- Implement classical efficiency tracking methods to evaluate plants comparatively or track efficiency over time.
- Implement DEA using various models as selected by user.
- Use DEA to track plant efficiency over a selected time window or between plants.
- Export results to Microsoft® *Excel*™ for easy viewing and analysis by user.
- Implement a functional and user friendly Graphical User Interface (GUI).
- Implement a portable and reusable software design.

The information above is reflected in the software application's use case diagram, shown by ***Figure 4-9***.

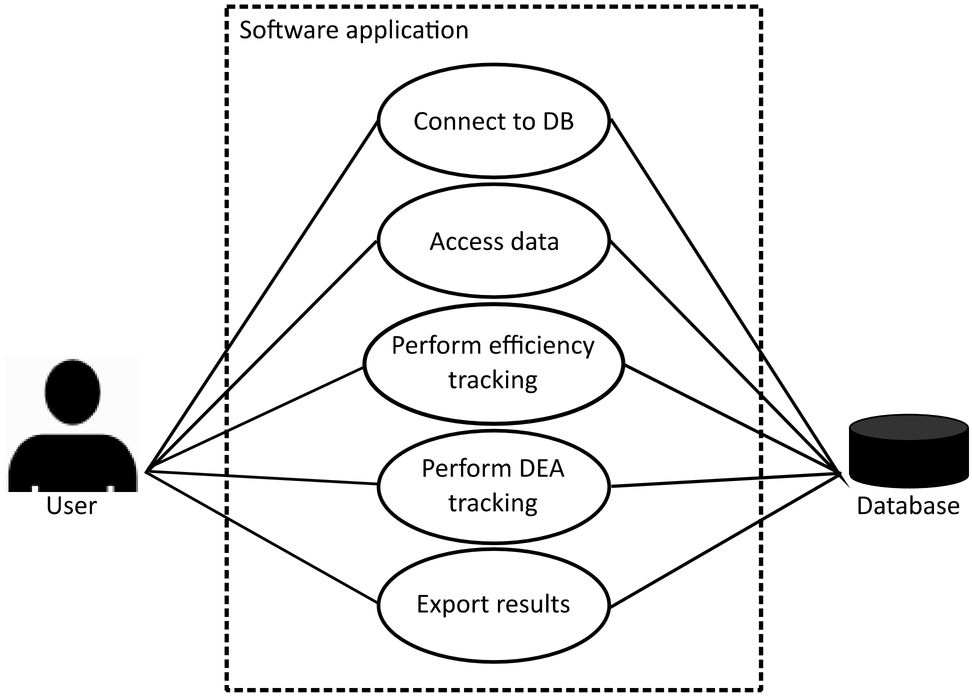


Figure 4-9*: Use case diagram for software application.*

4.3.2.2 Development risks

Significant risks arise during the design of the system, especially the system architecture. If the design does not make use of an adaptive and reusable design, then future alterations and extensions may not be possible, or would require significant modification to the existing system.

4.3.2.3 Transitional architecture

When approaching the design of the system architecture there are two basic models that can be selected. Either the entire system is contained in a single module or it is split into multiple separate modules which are called by and interact with a root module. The singular module design method has the advantage of being easier and less time consuming in its development. However, future extensions are difficult to integrate. Testing also becomes more complex, as it may be difficult to locate bugs in extensive code.

The modular method is far more complex to develop, as information needs to be passed between modules. However, this modular design lends itself to easy future expansion and the addition of modules. Also, the testing phase is significantly simpler as modules can be debugged separately. This method is thus selected for this project. The system is centred around the root module, which calls and interacts with individual component modules. The root module also creates the database connection which is carried over to the component modules. Additionally, the root module can export results to *Excel*™ or XML. ***Figure 4-10*** shows the transitional architecture and several modules, as well as the database connection and Export connection for exports. The flow of data in the application is also shown The advantages listed above show that this architecture is feasible and applicable to this project.

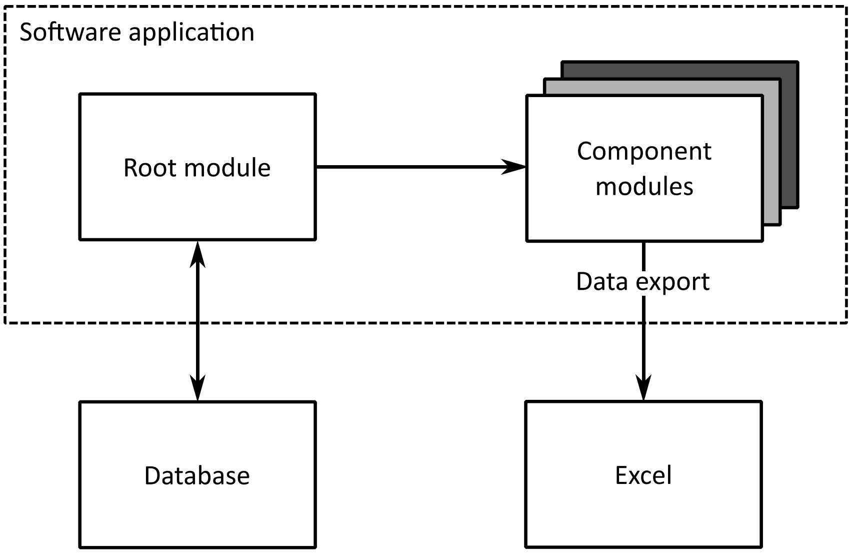


Figure 4-10*: Transitional system architecture showing application data flow.*

4.3.3 Elaboration phase

During this phase the functional requirements of the system are established. Additionally, the final system architecture is created. This architecture is the main output of the phase, along with a complete use case model.

4.3.3.1 Functional requirements

Listed below are the functional requirements for the software applications.

- A separate GUI for root module and each component module.
- A DEA engine capable of analysing the selected data.
- The functionality to export all results to *Excel* for user viewing and processing.

4.3.3.2 Final architecture

The final architecture is modular in nature, as is described in section 4.3.2.3. Each of the components have a unique GUI for the appropriate options and inputs required. The main components of the system are as follows:

- *Root module:* Manages all component modules. Also creates and passes on the database connection. The root module includes plant data access, which allows for the access, manipulation and importing of plant data.
- *Efficiency analysis module:* Uses classical efficiency evaluation methods to analyse plants over time or comparatively.
- *DEA engine module:* Performs actual DEA processes. Allows user to select the plant(s) to be analysed, which inputs and outputs are used, the time window and the DEA methodology to be followed. DEA results can be exported to *Excel*. Can also call the baseline formulator once analysis is complete and results are generated.

The final architecture, along with its connections to the database and *Excel* are shown in ***Figure 4-11***. A key for ***Figure 4-11*** is shown in ***Figure 4-12***, explaining the flow of data and how modules are called.

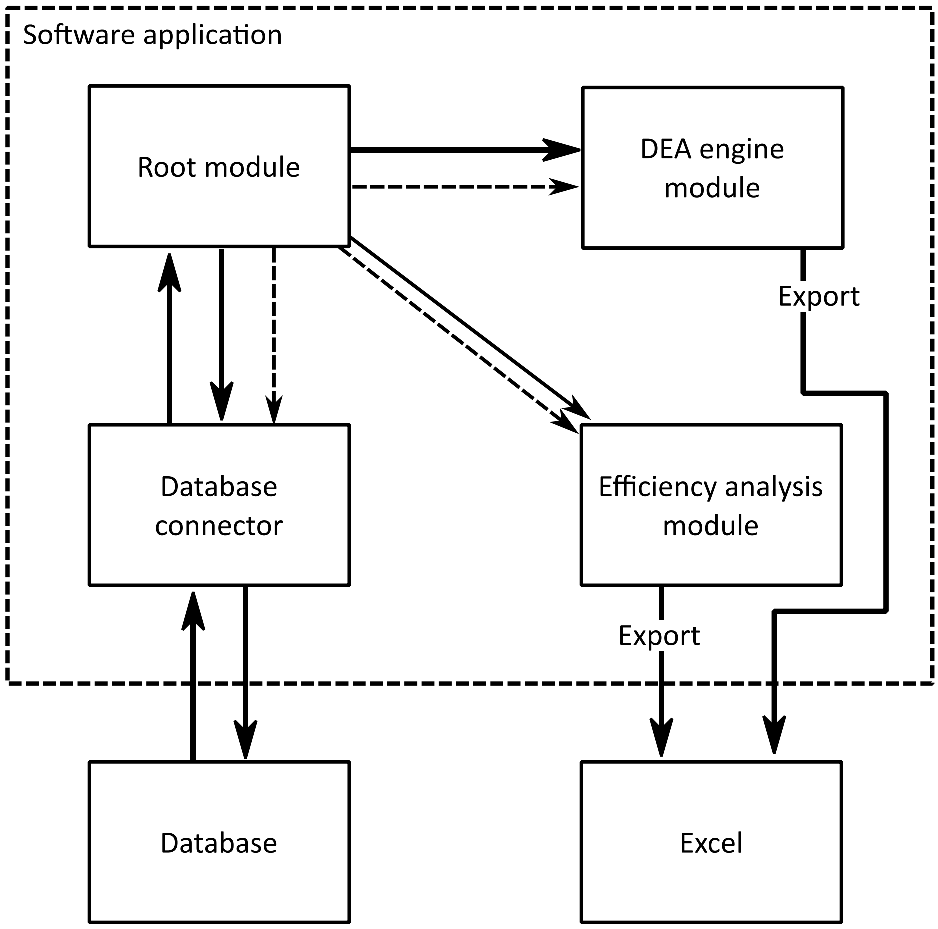


Figure 4-11: *Final software architecture.*

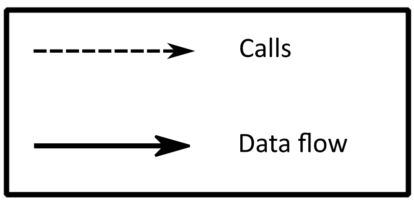


Figure 4-12: *Key for Figure 4-11.*

4.3.3.3 Module use case model

Each of the above-mentioned modules' use case diagram, collectively making up the complete use case model of the system is presented in this section. The use case diagrams are shown below in ***Figure 4-13*** to ***Figure 4-15***.

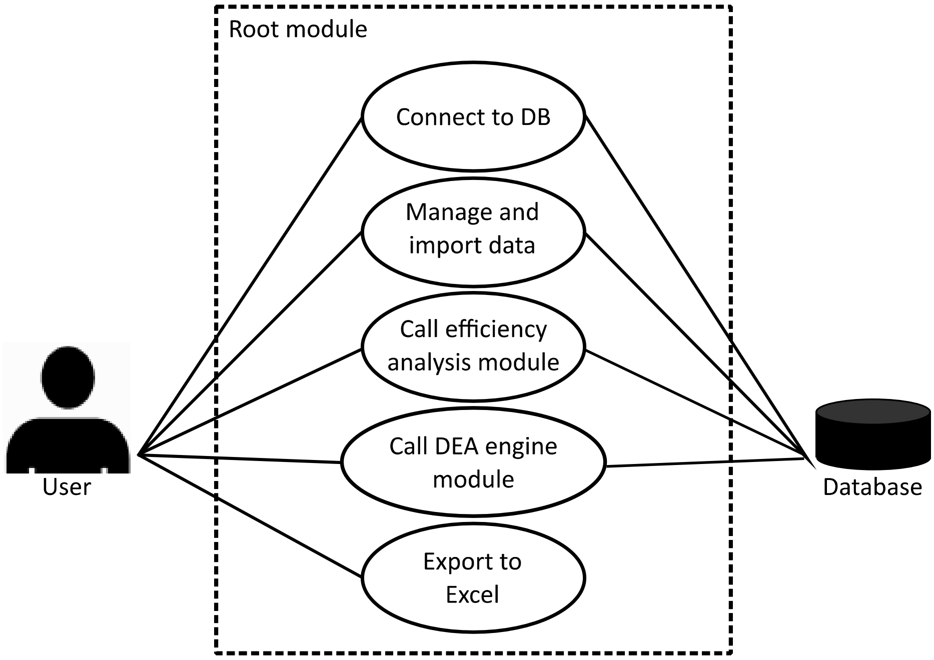


***Figure 4-13**: Use case diagram for root module.*

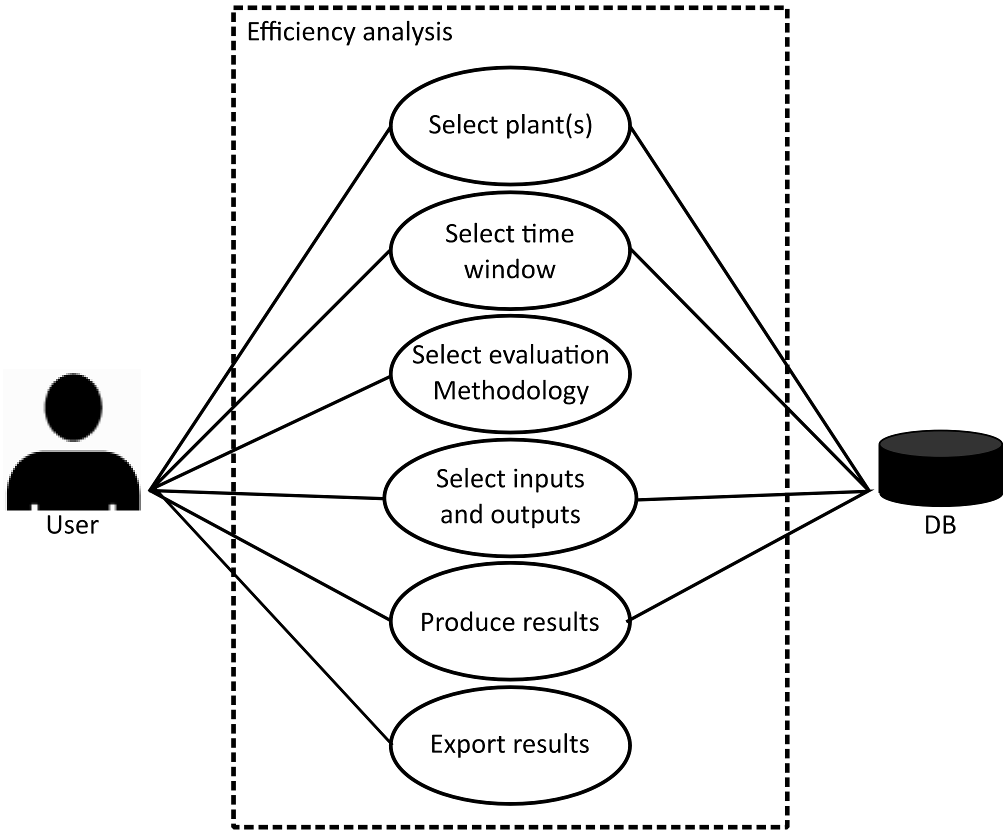


***Figure 4-14**: Use case diagram for efficiency analysis module.*

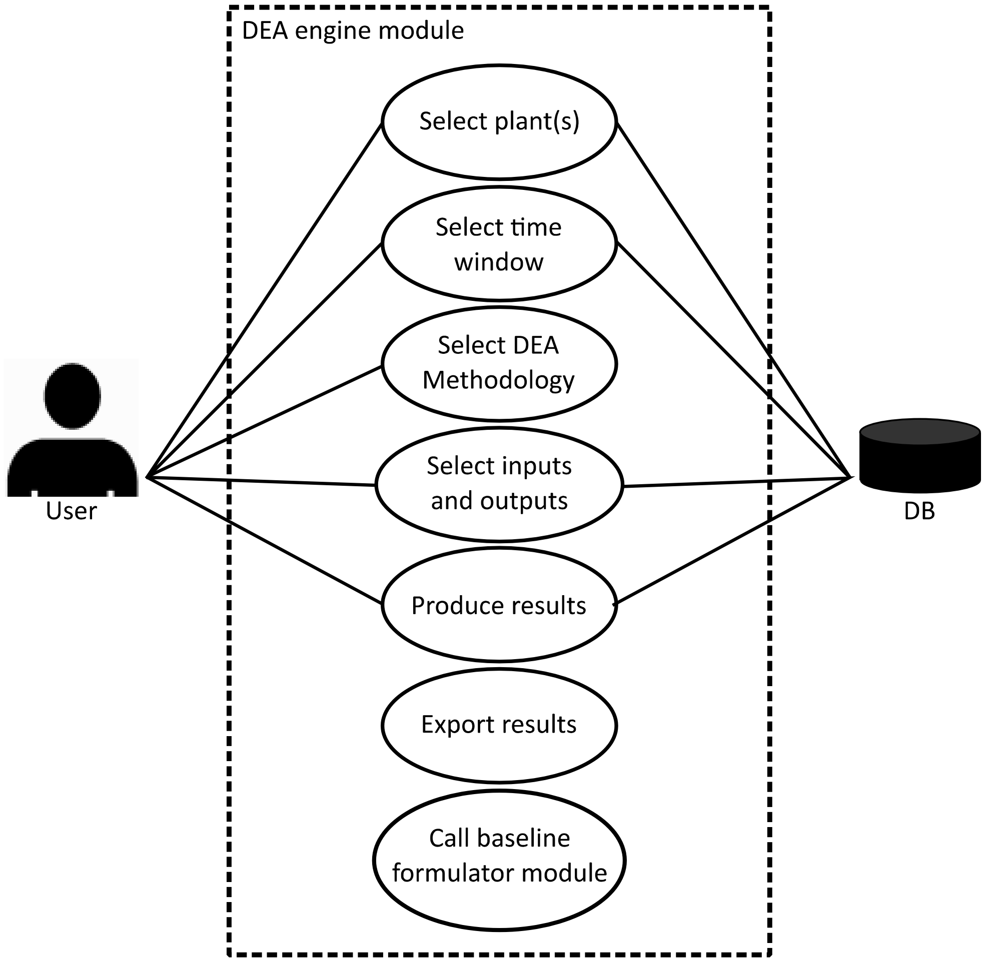


Figure 4-15*: Use case diagram for DEA engine module.*

4.3.4 Construction phase

During this phase the focus is on the design and implementation of the complete system software. The phase output consists of a fully functional "beta-version" of the system software. Also included in this section are the various activity diagrams for the root and component modules of the system. Each of the system components is implemented in Embarcadero Delphi™ for Microsoft® Windows™ operating system. The Delphi™ integrated development environment (IDE) and IDEs in general are covered in section 2.5. In this section each of the system modules and the activity diagrams are covered. ***Figure 4-16*** shows the key for activity diagrams.

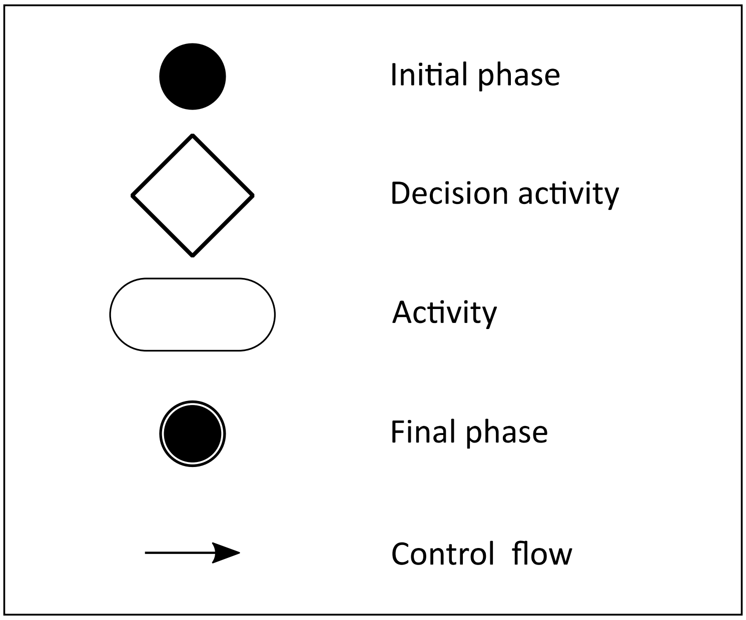


Figure 4-16*: Activity diagram key.*

4.3.4.1 Root module design and implementation

The root module acts as the "hub" of the system. It includes the following functionalities:

- Establishes database connection which can be carried over to component modules.
- Allows user to select desired project.
- Includes profile data manager and plant data import tools.
- Calls component modules.
- Exports results generated by component modules to *Excel*.

The root module allows the user to select the desired IP address where the required database is hosted. The correct username and password are required. The database connection is created as a Delphi™ *TMySQLConnection* object, which allows for easy passing to component modules. Once the connection is established the project can be selected and component modules can be called. The calling of component modules by the root module is illustrated in ***Figure 4-17***.

The root module also consists of a plant manager system that allows for the viewing, importing and manipulation of plant data, including plant, unit and profile data, as mentioned in section 4.2.

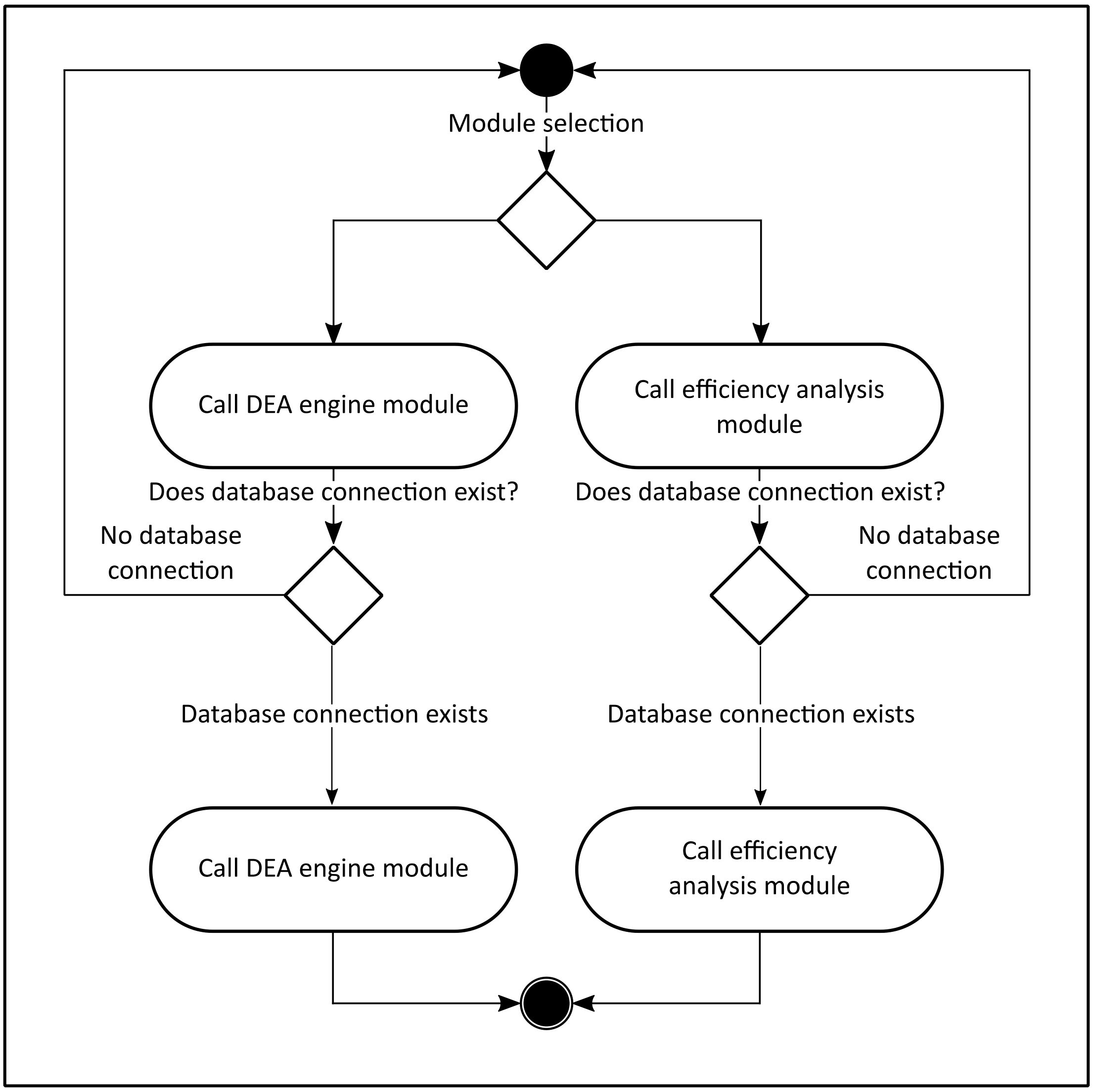


Figure 4-17*: Activity diagram for root module showing component module calls.*

4.3.4.2 Efficiency analysis module design and implementation

The efficiency analysis module allows the user to evaluate the efficiency of power plants using historical data. A single plant's efficiency can be tracked over time, or multiple plants can be evaluated comparatively. The functionalities of this module are shown below:

- Select project (if not selected in root module).
- Select plant(s).
- Select time window over which to perform the analysis.
- Select the efficiency evaluation method to use in analysis (heat rate, actual efficiency, technical efficiency or scale efficiency).
- Results are exported to *Excel*.

The DMU scale can be selected for each analysis. Plants can thus be evaluated on a daily, monthly or yearly scale. The overall average efficiency is evaluated for each plant, as well as the efficiency of each DMU. The module queries the relational database for all required data. A full activity diagram is shown for the efficiency analysis module in ***Figure 4-18***.

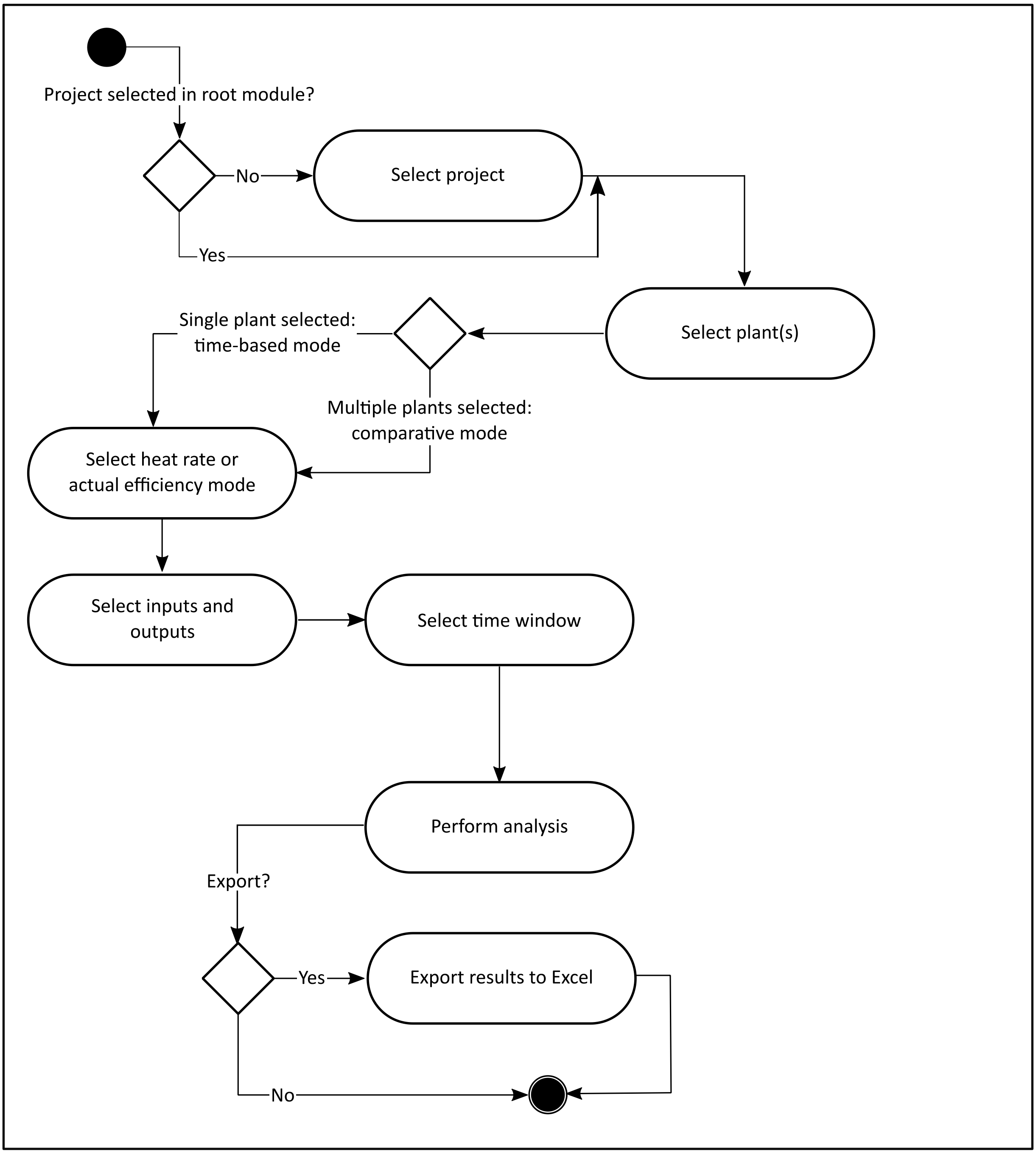


Figure 4-18*: Activity diagram for efficiency analysis module.*

4.3.4.3 DEA engine module design and implementation

The DEA engine module allows the user to perform DEA analyses on plant data. This may consist of only a single plant's data, in which case a time-based tracking analysis is performed, or multiple plants' data, in which case a comparative analysis is performed between plants. The functionalities of the DEA engine module are shown below:

- Select project (if not selected in root module).
- Select plant(s).
- Select time window over which to perform the analysis.
- Select the various DEA methodologies to use in analysis.
    - Select envelopment or multiplier model.
    - Select constant, variable, non-increasing or non-decreasing return-to-scale model.
    - Select input- or output-orientation.
- Select which inputs and outputs are used in analysis.
- In case of a time-based tracking analysis, the DMU scale is selected.
- Results can be exported to *Excel*.

When a single plant is selected, the plant data is evaluated over a time window, with time period serving as the individual DMUs. Thus, the individual months, weeks or days can be monitored comparatively. The DEA methodology is selected for the analysis. This includes both the envelopment or multiplier model, the return-to-scale mode and the option of output orientation. The necessary data is acquired from the relational database via the database connector using dynamic queries. The constraints associated with each individual DEA model are formulated by Delphi™ and passed to the *Lp_Solve51* DLL. Once all constraints are passed, the *solve* command is given. The linear programming results are read and stored by Delphi™. These interactions are shown in ***Figure 4-19***.

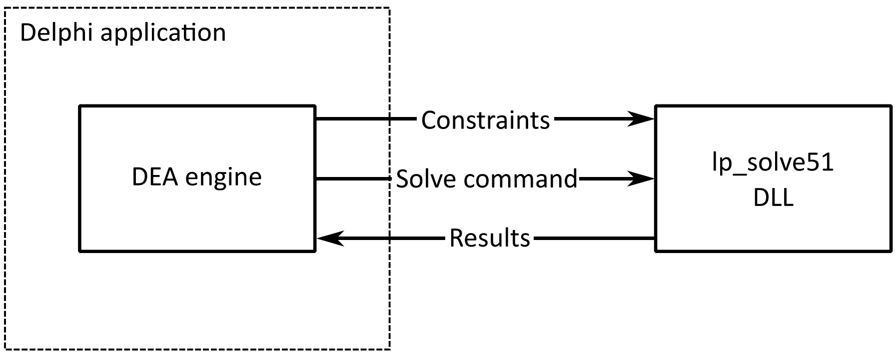


Figure 4-19*: DEA engine and lp_solve51 DLL interactions.*

Each DMU is solved as a separate LP problem. Constraints are formulated according to the DEA model and orientations selected, based on the mathematical basis of each methodology. The various structures of the constraints are described below. The *Lp_Solve51* DLL requires constraints to be passed as strings with the inequality specified afterwards. Variables are identified by parsing these strings. For the envelopment model, all constraint strings take the form of Equation (4.1) , i.e. an overall efficiency variable plus one λ variable per DMU.

$$[\theta_1 \; \lambda_1 \; \lambda_2 \ldots \lambda_N] \tag{4.1}$$

where

θ_i denotes the efficiency of i^{th} DMU,
and
λ_N denotes the weight associated with the N^{th} DMU,
The variables shown in 4.3.4.1.2.1.1 are the ones identified by the *Lp_Solve51* DLL. The objective function for the envelopment model involves the minimising of the θ value, so the objective function takes the form of Equation (4.2).

$$Minimise: \; [\theta_1 \; 0 \; 0 \ldots] \tag{4.2}$$

For each DMU a constraint needs to be added per input category and per output category, as covered in section 3.3.6. For DMU *o* these take the form of Equation (4.3) to (4.8).

$$[-x_{o1} \; x_{11} \; x_{21} \ldots x_{N1}] \leq 0 \tag{4.3}$$
$$[-x_{o2} \; x_{12} \; x_{22} \ldots x_{N2}] \leq 0 \tag{4.4}$$
$$\vdots$$
$$[-x_{oN} \; x_{1N} \; x_{2N} \ldots x_{NN}] \leq 0 \tag{4.5}$$
$$[0 \; y_{11} \; y_{21} \ldots y_{N1}] \geq y_{11} \tag{4.6}$$
$$[0 \; y_{12} \; y_{22} \ldots y_{N2}] \geq y_{12} \tag{4.7}$$
$$\vdots$$
$$[0 \; y_{1N} \; y_{2N} \ldots y_{NN}] \geq y_{1N} \tag{4.8}$$

These constraints are repeated for each DMU as a separate LP problem. Further constraints are required in the following forms.

$$[1 \; 0 \; 0 \ldots 0] \geq 0 \tag{4.9}$$
$$[0 \; 1 \; 0 \ldots 0] \geq 0 \tag{4.10}$$
$$\vdots$$
$$[0 \; 0 \; 0 \ldots 1] \geq 0 \tag{4.11}$$
$$[1 \; 0 \; 0 \ldots 0] \leq 1 \tag{4.12}$$

Equations (4.9) to (4.11) ensure that all variables are non-negative, while Equation (4.12) ensures that the efficiency value is always less than one, and therefore always a value between zero and one.

The Return to Scale (RTS) orientation is determined by the addition of a separate constraint, as shown in Equation (4.13). The inequality assigned to this term dictates the RTS orientation, as shown in Equation (4.14) to (4.16) and as described in section 3.3.6.4. If Equation (4.13) is unbound the RTS is constant.

$$[0\ 1\ 1\ \dots\ 1] \tag{4.13}$$
$$Variable:\ [0\ 1\ 1\ \dots\ 1] = 1 \tag{4.14}$$
$$Non\ increasing: [0\ 1\ 1\ \dots\ 1] \leq 1 \tag{4.15}$$
$$Non\ decreasing::\ [0\ 1\ 1\ \dots\ 1] \geq 1 \tag{4.16}$$

The multiplier model mathematical formulation is covered in section 3.3.5. For this model, constraints are still passed as strings however in a slightly different format, as shown in Equation (4.17) for a specific DMU with *i* inputs and *N* outputs. A *v* variable is added for each input category and a *u* variable is added for each output category.

$$[v_1\ v_2\ \dots v_i\ u_1\ u_2\ \dots u_N] \tag{4.17}$$

where

v_i denotes the weight associated with the i^{th} input category,
and
u_N denotes the weight associated with the N^{th} output category.
The objective functions for the input and output orientated multiplier models are shown in Equation (4.18) and (4.19) respectively. For the input orientated form Equation (4.19) must hold true, so as to keep outputs constant, while for the output orientated form Equation (4.21) must hold true, so as to keep inputs constant.

$$maximise: [0\ 0\ \dots 0\ y_1\ y_2\ \dots y_N] \tag{4.18}$$
$$minimise: [x_1\ x_2\ \dots x_i\ 0\ 0\ \dots 0] \tag{4.19}$$
$$[x_1\ x_2\ \dots x_i\ 0\ 0\ \dots 0] = 1 \tag{4.20}$$
$$[0\ 0\ \dots 0\ y_1\ y_2\ \dots y_N] = 1 \tag{4.21}$$

For the input orientated form constraints take the form of Equations (4.22) to (4.24). For each DMU *n* constraints need to be added, where *n* is the total number of DMUs in the analysis. A DMU with *i* inputs and *N* outputs is considered.

$$[-v_{11}\ -v_{12}\ \dots -v_{1i}\ u_{11}\ u_{12}\ \dots u_{1N}]\ \leq 0 \tag{4.22}$$
$$[-v_{21}\ -v_{22}\ \dots -v_{2i}\ u_{21}\ u_{22}\ \dots u_{2N}]\ \leq 0 \tag{4.23}$$
$$\vdots$$
$$[-v_{n1}\ -v_{n2}\ \dots -v_{ni}\ u_{n1}\ u_{n2}\ \dots u_{nN}]\ \leq 0 \tag{4.24}$$

For the output-orientated form, constraints are formulated as in Equation (4.25)to (4.27).

$$[v_{11}\ v_{12}\ \dots v_{1i} - u_{11} - u_{12}\ \dots -u_{1N}]\ \leq 0 \tag{4.25}$$
$$[v_{21}\ v_{22}\ \dots v_{2i}\ -u_{21}\ -u_{22}\ \dots -u_{2N}]\ \leq 0 \tag{4.26}$$
$$\vdots$$
$$[v_{n1}\ v_{n2}\ \dots v_{ni}\ -u_{n1} - u_{n2}\ \dots -u_{nN}]\ \leq 0 \tag{4.27}$$

Once the constraints are passed to the *Lp_Solve51* DLL the solve command is given. Results are stored in temporary tables on the database for use in *Excel*™ exporting or by baseline formulator module. These temporary tables are destroyed on termination of the application. Exported results include the following:

- Name of plant being analysed.
- Current date and time.
- Start and end time of selected time window.
- Names of each DMU being analysed.
- Number of iterations in linear programming optimisation.
- Number of variables identified.
- Calculated overall efficiency.
- Name and value of each calculated weight (depends on model selected).

A full activity diagram for the DEA engine module is show in ***Figure 4-20***.

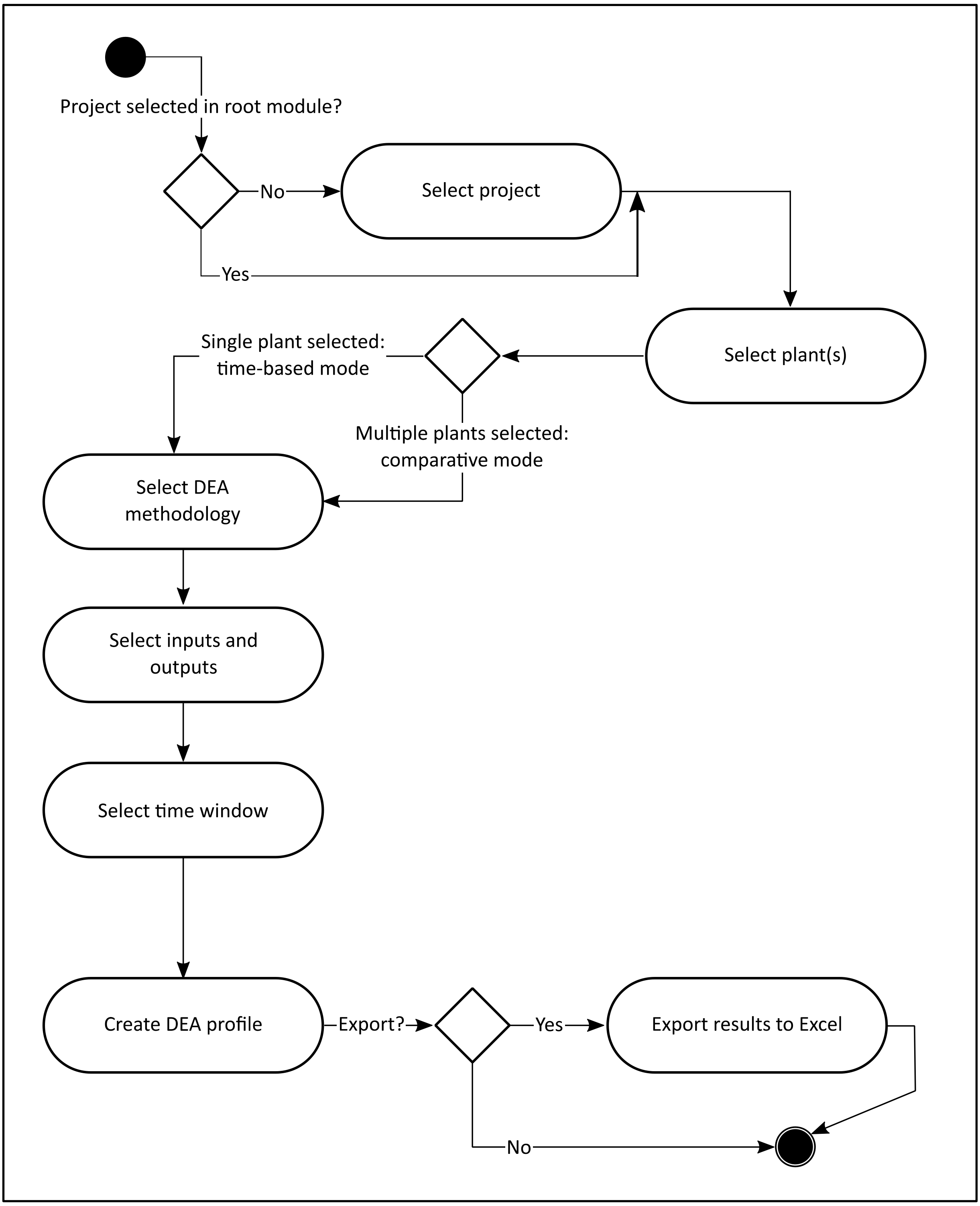


Figure 4-20*: Activity diagram for DEA engine module.*

4.3.4.4 Application testing

Rigorous testing of each module is necessary to ensure correct working and stability. As specified by the Unified Process, testing is iterative in nature i.e. bugs are identified and rectified before the next round of testing commences. This process is repeated until the implemented application meets all its requirements.

The implemented application and all included modules are tested using model data. This data is stored in a test database, constructed as described in section 4.2 as a test project. Multiple test plants are included, each consisting of number of units and profiles. A model timeline is also created. The complete database is hosted using *WAMPserver.* To test the validity of the application's temporary database tables, an external application is employed. Temporary tables are manually viewed using *MySQL Query Browser.*

The root module's primary functions consist of establishing a database connection to be passed to component modules and to call these component modules. The database connection feature is tested by establishing a connection to the test database. By successfully calling each individual component module, the root module is further tested.

The efficiency analysis component module must retrieve the relevant historical plant data from the relational database as selected by the user. Efficiency is evaluated using this data. Results are calculated manually in *Excel* and compared to the applications results, thus testing their accuracy.

The DEA engine component module must query the database and retrieve the necessary data for the selected analysis. This data is used to construct constraints which are passed to an external linear programming DLL. This DLL is given the solve command and the results are retrieved. These results are saved in temporary database tables and potentially exported to *Excel*.

By querying and extracting data from the database the module's connection is tested. Constraints are formulated and printed to a dedicated debug window to test their structure. The DLL receives these constraints and returns results, confirming the module's ability to communicate with the DLL. The results are again printed to the debug window. The linear programming problem used for testing is purposely selected to be simple in nature so that the results' accuracy can be confirmed by calculation in *Excel*. Temporary tables are viewed and their accuracy confirmed in *MySQL Query Browser*. Results are exported to *Excel*™ and viewed again, confirming the correct structure and validity of results.

4.3.5 Transition phase

During the transition phase, the application is released and placed in the user domain. Initial users are viewed as *beta testers*, their feedback and error reporting serves as thorough software testing.

The final stage of software development in this project consists of the application's use in the project case studies.

5 Case studies

5.1 Research objectives and analysis methodology

The case studies are performed using historical data for the target South African plant. For comparative benchmarking, historical data for two additional US coal fired plants is utilised. The first of the US plants is selected to be of similar age, technology and rated capacity as the South African plant, so as to draw meaningful comparisons in results. The second US plant is a more modern coal-fired plant, so as to compare efficiency results with the other older plants. At the time of writing all three plants are operational and providing electrical energy to their respective regional grids. The case studies aimed to achieve the following research objectives listed in section 1.3.2. Historical data is provided in monthly intervals. This data is imported and stored in the implemented relational database for access by the implemented software application.

5.1.1 Data acquisition

Data for the target South African coal fired power plant is supplied by the utility. This data includes coal consumption, fuel oil consumption, fuel calorific values, generated and sent-out electrical energy for the period January 2012 to December 2013. Coal moisture content data is provided for the period January to December 2012. Coal usage, fuel oil usage, auxiliary electrical energy usage, and sent-out electrical energy is provided in daily intervals, as well as coal calorific, sulphur and ash content data. Other datasets are provided in monthly intervals. South African weather data is supplied by the *South African Weather Service®*. This data includes average monthly maximum temperature and monthly total rainfall.

Historical data for the US plants is acquired from the *US Energy Information Administration (EIA) Independent Statistics and Analysis* web portal. This dataset consists of the total monthly primary fuel usage (coal in both cases, measured in thousands of US tons), total monthly secondary fuel usage (distillate fuel oil for Plant B or natural gas for Plant C, measured in thousands of barrels or thousands of cubic feet respectively), total sent-out electrical energy in MWh. Calorific values for all fuels are also available, as well as the average sulphur and ash content of the fuel consumed. US weather data is acquired from the *National Oceanic and Atmospheric Administration (NOAA) National Centers for Environmental Information* web portal. This data includes average monthly maximum temperature (in degrees Fahrenheit) and total monthly rainfall (in inches). The historical data was added to a relational database as described in section 4.2. The data is arranged by relevant plants, units and profiles. Additional plant details are also stored.

5.2 Plant configurations

The case study includes three different plants so as to test the proposed methodology in more than one context. A brief description of each plant is provided below. Plant A, B and C are summarised in Table 5-1.

5.2.1 Plant A

Plant A is a coal fired power plant, located in Mpumalanga, South Africa. Plant A is the project's target plant, and remains the focus of the study. The plant consists of six units, rated 200MW each for a total plant capacity of 1200MW, and was commissioned in 1969. Four of the plant's units are conventional wet cooling with the remaining two making use of dry cooling. The plant utilises low-calorific value coal, typically sub-bituminous in quality, but also consumes smaller amounts of distillate fuel oil and is designed for a rated efficiency of 32,90%. Energy Efficiency (EE) interventions were conducted near the end of 2012, attempting to increase the efficiency of the plant.

5.2.2 Plant B

Plant B is a coal fired power plant, located in Texas in the US. The plant consists of three units, rated 558MW each for a total plant capacity of 1674MW. The plant's first unit started producing electrical energy in 1977. The plant uses sub-bituminous quality coal as a primary fuel and distillate fuel oil as a secondary fuel.

5.2.3 Plant C

Plant C is a coal fired power plant, located in Wisconsin in the US. The plant consists of two units of 701MW each for a total plant capacity of 1402MW. Although the plant was constructed in the 1950s, all its original units were retired before 2010 and replaced by the two newer units. The plant's first new unit was completed in 2010 and the second in 2011. The plant uses sub-bituminous quality coal, but also uses natural gas as a secondary fuel.

Table 5-1*: Plants analysed in case study.*

	Plant A	**Plant B**	**Plant C**
Location	Mpumalanga, SA	Texas, USA	Wisconsin, USA
Primary fuel	Sub-bituminous coal	Sub-bituminous coal	Sub-bituminous coal
Secondary fuel	Distillate fuel oil	Distillate fuel oil	Natural gas
Units	6	3	2
Plant Capacity	1200MW	1674MW	1402MW
Commission date	1969	1977	2010

5.3 Summary of case studies

The developed software application and relational database are utilised in each case study. A separate set of case studies is performed for classical efficiency evaluation, regression analysis and DEA efficiency evaluation. Each of these is expanded on below.

5.3.1 Overview of classical energy efficiency evaluation case studies

In this section classical efficiency evaluation methods are used to investigate plant performance. Various plants and time periods are considered. The case studies performed are summarised below.

- *Daily EE tracking*: The performance of Plant A (the target plant) is tracked on a daily basis from 1 January 2012 to 31 December 2013. This is done to investigate the impact of EE interventions performed at the end of the first year.
- *Monthly EE tracking*: The EE of the three case study plants is evaluated comparatively and individually. The analysis is performed on a monthly basis over a two year period. Plant A's performance is compared to that of the US plants. Seasonal trending is investigated and compared between plants.
- *EE tracking with data averaging*: The EE of the three case study plants is examined using averaged datasets. This consists of both data averaged on three month intervals, as well as data averaged over two years. Plant performance is compared and trending investigated.

5.3.2 Overview of regression analysis case studies

In this section regression analysis' use in plant efficiency evaluation is investigated. The various case studies performed are summarised below.

- *Regression analysis for coal moisture results:* A regression analysis is performed to further examine the effect of coal moisture on overall plant performance.
- *Regression analysis for monthly average capacity factor:* A regression analysis is performed to further examine the effect of varying capacity factor on plant efficiency.
- *Regression analysis for coal calorific content:* A regression analysis is performed to establish the extent to which coal calorific content can effect plant efficiency.

5.3.3 Overview of DEA energy efficiency tracking case studies

Various case studies are performed in order to examine the overall use of DEA as a tool in tracking power plant efficiencies in various contexts. These case studies are summarised as below.

- *DEA return-to-scale investigation for EE tracking:* Various orientations of DEA return-to-scale are investigated to establish the suitability of each in a plant EE tracking context. The suitability of the various RTS orientations is determined by examining the root-means-square-error (RMSE) and correlation with actual normalised energy efficiency data.
- *DEA EE tracking:* DEA's use as a tool for tracking plant EE is examined by comparing the efficiency of the three case study plants. The results of the DEA are compared to the actual

EE of each period for each plant. Plants are also evaluated individually over the time period from 2012 to 2013. The consistency of each plant's performance is investigated.

- *DEA efficiency tracking using fuel mass and calorific content:* Case study plants are evaluated using the mass and calorific values of fuel consumed. The effect of fuel mass and calorific content is investigated by incorporating these datasets using DEA. The analysis takes place on a monthly basis from 2012 to 2013. The consistency in case study plant performance is also investigated.
- *DEA efficiency tracking with climate factors:* The effect of rainfall and temperature on case study plants' efficiency is investigated. Coal moisture content is incorporated into a DEA for Plant A on a monthly basis over the 2012 year.
- *DEA efficiency tracking with capacity factor:* The effect of the capacity factor at which case study plants are operating on overall efficiency is investigated. A DEA is performed for Plant A that incorporates its capacity factor dataset over the 2012/2013 year.
- *DEA eco-efficiency tracking:* The environmental/emissions "cost" of higher energy efficiency is evaluated for all three case study plants using DEA, both individually and comparatively. The analysis is performed from 2012 to 2013.
- *DEA efficiency tracking with monthly averaging:* A three month moving average is applied to all plant datasets. This is done to potentially eliminate inaccuracies caused by coal content and quantity measurement procedures. The previous DEA EE, moisture content, fuel mass and calorific value, and eco-efficiency analysis are repeated using the averaged datasets.
- *DEA efficiency tracking with calendar year averaging:* 2012 and 2013's data are averaged on a monthly basis for all three case study plants. This is done to potentially make seasonal trends more visible. DEA EE, and fuel mass and calorific content analyses are repeated using the new averaged datasets.

5.4 Classical efficiency tracking analysis results

5.4.1 Overview

This section presents the results of classical EE analyses performed for the three case study plants. These studies are performed to evaluate the efficiency of the three plants, as well as to serve as a base case to evaluate the use of the DEA case studies presented in the next section

5.4.2 Daily classical energy efficiency tracking

In this section Plant A's efficiency is tracked on a daily basis from 1 January 2012 to 31 December 2013. Plant A's dataset is provided in daily intervals, while for Plant B and Plant C only monthly intervals are available. Results are shown in Appendix A.1 in Table A-1. Results of actual efficiency analysis are shown visually in Figure 5-1.

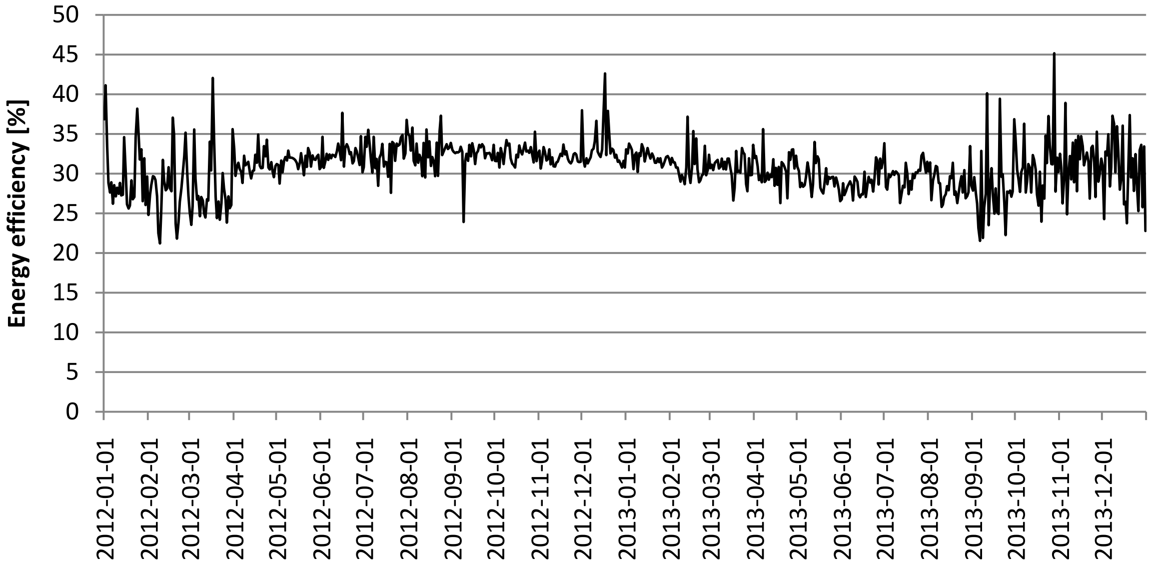


Figure 5-1*: Daily actual efficiency for Plant A.*

Plant A's efficiency becomes far less consistent in the first and last 4 months of 2013. The number of outliers also increased in these months, often reaching close to 40% efficiency or more. This is hypothesised to be due to measurement inaccuracies, as this level of efficiency is unattainable for a plant of this vintage and design. The average efficiency was generally lower than average during these months. When data is investigated, it is found that outliers are present in both the calorific content and the fuel mass usage datasets. The scheduled interventions during 2012 for Plant A include both new coal analysis equipment as well as mass measurement equipment, which proves these datasets as potentially inaccurate and the likely source of the outliers. The most major EE intervention took place between 01 September 2012 and 30 November 2012, focusing on steam feed pumps for unit 2 and 3. Unit 2 was run throughout this period while unit 3 was stopped during most of October 2012. A sharp dip in efficiency took place at the beginning of September, which may be the result of the commencement of the steam pump EE intervention. Another major intervention took place during November 2012, which focused on the sealing of steam pipes for unit 6. Unit 6 did not operate for most of this month, however overall plant efficiency did not deviate sharply from average.

5.4.3 Monthly classical energy efficiency tracking

The energy efficiency of each plant is first investigated. This is done on monthly intervals for the 2012 to 2013 period. The dataset used in this analysis are shown in ***Table 5-2***.

***Table 5-2**: Inputs and outputs used in results of EE analysis between plants.*

Inputs	**Outputs**
Total energy consumed [MJ]	Total electrical energy sent out [MJ]

The MJ input includes all fuel sources consumed, as well as auxiliary electrical plant energy (where available). The monthly average energy efficiencies of the three plants are shown in Appendix A.2 in ***Table A-2***. These efficiencies are represented visually in Figure 5-2.

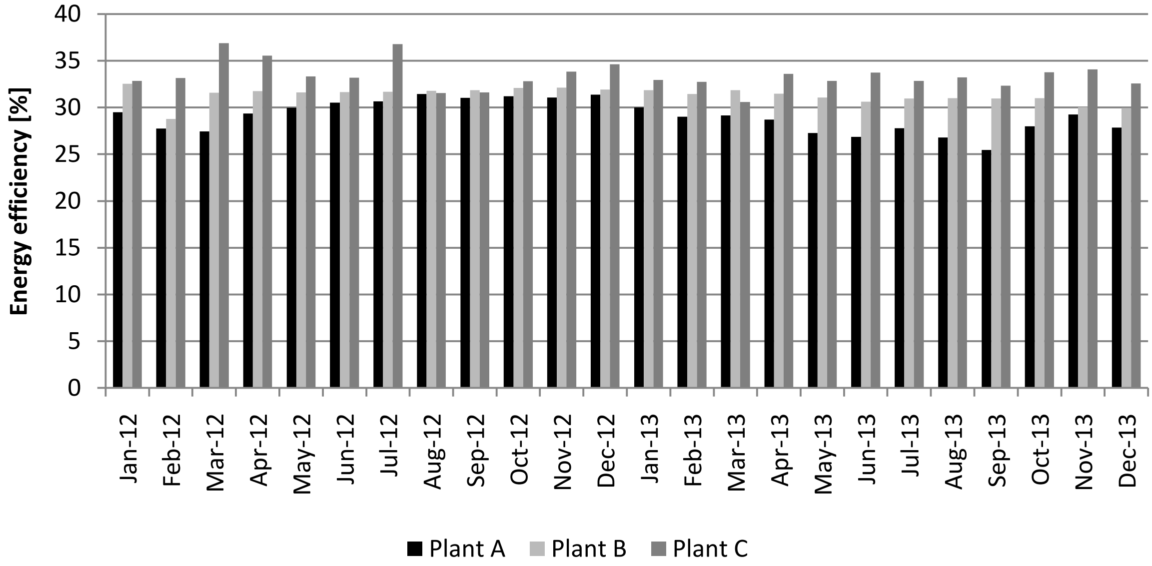


***Figure 5-2**: Monthly energy efficiencies of Plant A, Plant B and Plant C.*

At 29,24%, Plant A has a significantly lower average energy efficiency than that of Plant B and Plant C, which score 31,32% and 33,40% respectively. Plant C is the most advanced plant, but is annually also subjected to less rainfall and a far lower average temperature than Plant A or Plant B, which could explain the higher average efficiency. Although rainfall data is fairly erratic for all three plants, temperature is more consistent. None of the plants show any significant correlation with temperature or rainfall datasets. The monthly variations from average are shown in ***Figure 5-3***. Despite having more than one major outliers, Plant B performs the most consistently, while Plant A shows the most erratic variations. As mentioned above, Plant C is far more advanced than both Plant A and Plant B and this result is unexpected. None of the available datasets showed any similar fluctuations between the plants, so it is hypothesised that the inconsistent variation in Plant C's efficiency is a results of operating conditions. Examining the similarities in seasonal trending between the plants, Plant A and Plant B follow a fairly similar trend with 57,35% correlation, while Plant C seems more unique in this aspect.

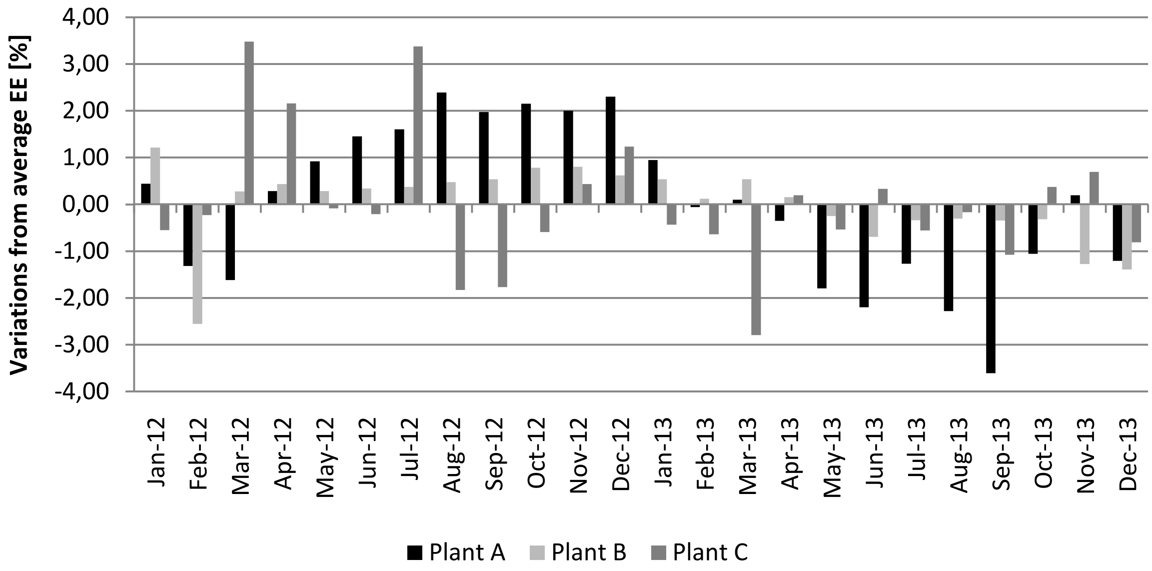


***Figure 5-3**: Monthly variations from average EE for case study plants.*

Despite the EE interventions in the later months of 2012, Plant A's average efficiency is significantly higher during 2012 when compared to 2013 (more than 2% higher), although the average consistency does not vary significantly between the two years. There were multiple small-scale EE interventions during 2013, the implementation of which may have led to decreased plant productivity and thus decreased EE. During 2013 rainfall was significantly higher in Plant A's vicinity, which may have caused a significant increase in coal moisture content (the coal moisture dataset only covers 2012). In addition, the average capacity factor of Plant A was 5% higher in 2013 in comparison to 2012. Plant A shows a fairly strong negative correlation between coal consumed (both in tons or in MJ) and efficiency (-54,12% and -59,47% respectively). This may be evidence that Plant A is more efficient when operating at a lower load. Interestingly, Plant B shows very strong positive correlations between coal consumption and efficiency (99,10% for coal in tons and 98,78% for coal in MJ). Plant B has a much higher average capacity factor when compared to Plant A, at 64,78% to Plant A's 58,63%. Plant B's may be designed to perform better at a higher load. None of the plants show any significant correlation between efficiencies for 2012 and 2013, which may indicate that environmental factors played little to no role in efficiency variations.

The effect of Plant A's various units on overall efficiency is now examined, by including up-time data for Plant A's six units. This data is shown in Appendix A.2 in ***Table A-3***. The correlation between each unit's up-time and Plant A's EE is examined and shown in ***Table 5-3***.

***Table 5-3**: Correlation between Plant A EE and unit up-time.*

unit 1	unit 2	unit 3	unit 4	unit 5	unit 6
-72,31%	81,40%	-19,46%	54,18%	-26,26%	4,71%

Interestingly, neither of the dry cooled units show significant correlation with EE. Unit 1 and 2 show the most significant results, with unit 1 having a strong negative correlation and unit 2 a strong positive correlation. It is hypothesised that unit 2 and unit 4 are the most efficient, hence their strong positive correlations.

5.4.4 Classical energy efficiency tracking with monthly averaging

The data for all three case study plants is averaged over a three month period so as to examine the effect on efficiency trending. Results are shown in ***Figure 5-4***. Plant A and Plant B again show similar trends with a correlation of 77,93%. Neither plant shows any significant correlation with their relevant regions' temperature or rainfall datasets. However, Plant A shows a strong negative correlation with coal moisture content at -77,24%. The coal moisture content dataset shows no significant correlation with the rainfall dataset though, bringing the accuracy of this dataset into question. ***Figure 5-5*** shows the monthly variations for the case study plants with monthly averaging.

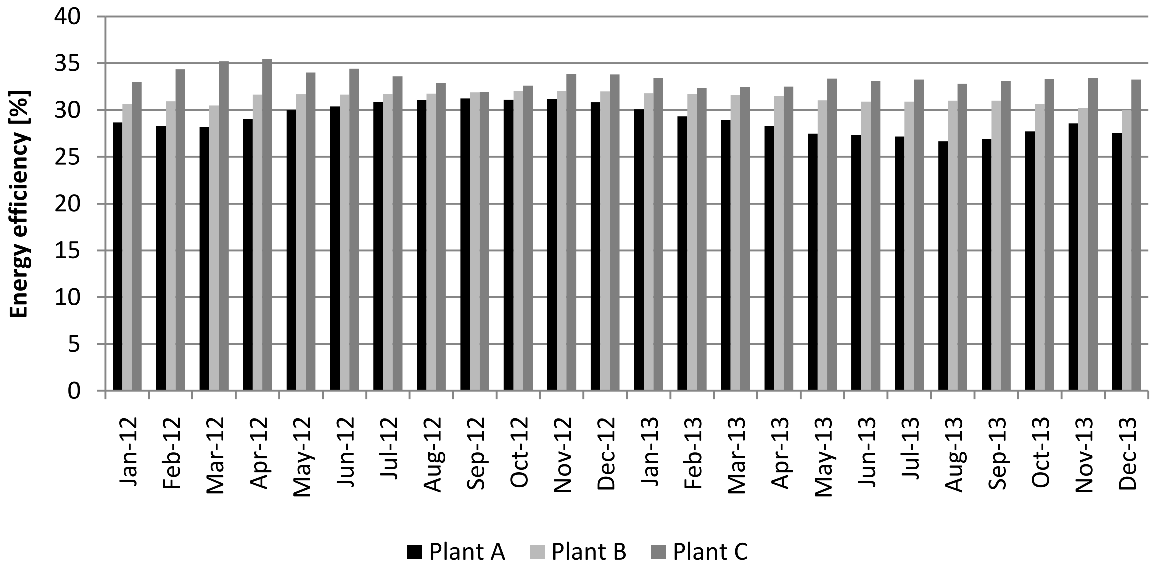


***Figure 5-4**: Energy efficiency for case study plants with monthly averaging.*

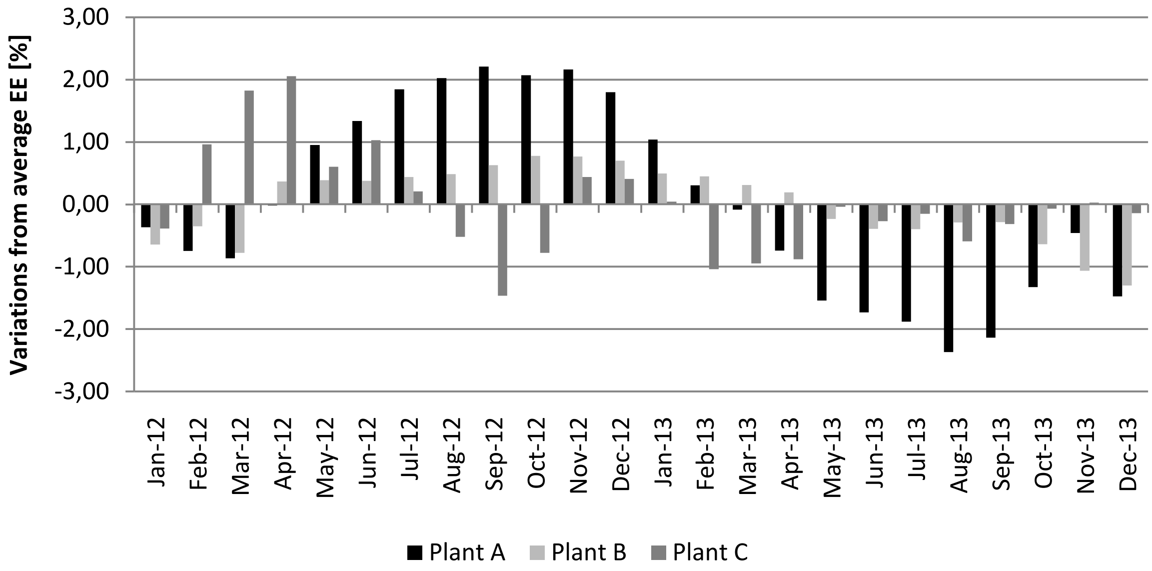


Figure 5-5: *Monthly variations from average EE for case study plants with monthly averaging.*

5.4.5 Classical energy efficiency tracking with two year averaging

Data from all three case study plants is averaged over two on a monthly basis. Results are shown visually in ***Figure 5-6***. Examining trending of the case study plants, Plant A now shows no significant correlation with either Plant B or Plant C. ***Figure 5-7*** shows the deviations from mean for the case study plants. Despite its high average efficiency, Plant C's output fluctuates far more than that of Plant A or Plant B. Plant A shows no significant correlation with any of the climate datasets.

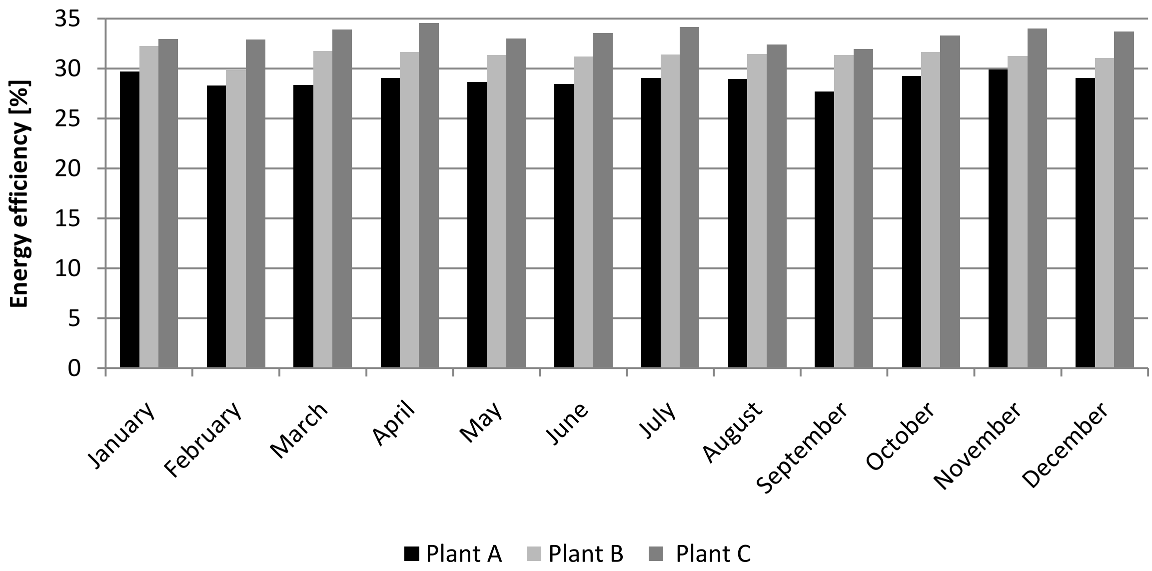


Figure 5-6: *Energy efficiency for case study plants with two year averaging.*

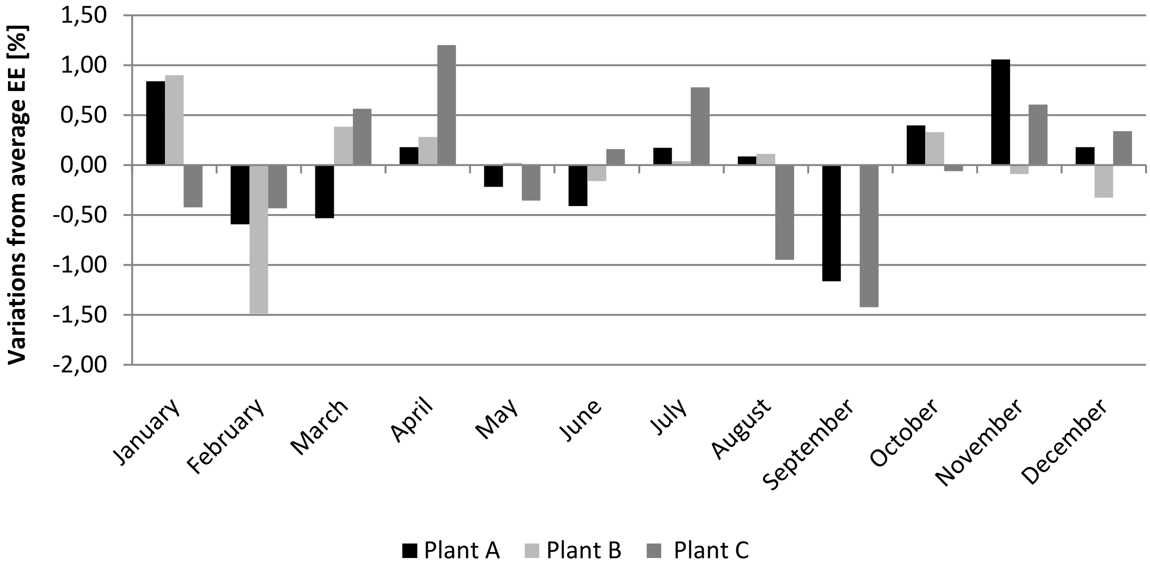


Figure 5-7*: Monthly variations from average EE for two year averaging.*

5.5 Regression analysis of classical efficiency results

5.5.1 Overview

To further investigate the effects of various environmental and operational factors on plant efficiency, a number of regression analyses are performed. The focus remains on the target plant (Plant A). Also, in an M&V context regression can be used for baseline adjustments. Each analysis considers datasets in their normal, three month- and yearly averaged forms. Exponential, linear, logarithmic, power and 2nd order polynomial regressions are all considered, and the R^2 value is shown for each, allowing the accuracy of the model to be evaluated. As EE is the dependent variable in each regression, it is represented by *y*, while the relevant additional variable is represented by *x.* Case studies are performed on all datasets that showed significant correlations. The temperature, rainfall and emission datasets were not included in the regression analysis, as they did not produce significant correlations.

5.5.2 Regression analysis for coal moisture content data

In this section a regression analysis is performed for Plant A using EE and coal moisture datasets. As the coal moisture content dataset only included values for 2012 the yearly averaged data was excluded. Results are shown in ***Table 5-4***. The monthly averaging data produced results with higher R^2 values. The second order polynomial produced the best results in both cases.

Table 5-4*: Results of regressions for Plant A EE vs. coal moisture content.*

	Normal	Monthly averaging

	Equation	R^2	Equation	R^2
Exponential	$y = 0{,}458e^{-5{,}16x}$	0,287	$y = 0{,}190e^{-2{,}82x}$	0,334
Linear	y = -1,524x + 0,425	0,288	y = -0,232x + 0,151	0,336
Logarithmic	y = -0,12ln(x) - 0,012	0,29	y = -0,06ln(x) - 0,001	0,34
2nd order polynomial	$y = 56{,}91x^2 - 10{,}85x + 0{,}806$	0,297	$y = 16{,}55x^2 - 10{,}07x + 1{,}613$	0,411
Power	$y = 0{,}103x^{-0{,}42}$	0,289	$y = 0{,}029x^{-0{,}84}$	0,337

5.5.3 Regression analysis for monthly average capacity factor

A regression analysis is now performed for capacity factor to gain further insight into its effect on EE. Results are shown in ***Table 5-5***. Monthly averaged datasets again produced the most accurate results. Interestingly, yearly averaged datasets produced the least accurate results, failing to find a solution for logarithmic and power curves.

Table 5-5*: Results of regressions for Plant A EE vs. capacity factor.*

	Normal		Monthly averaging		Yearly averaging	
	Equation	R^2	**Equation**	R^2	**Equation**	R^2
Exponential	$y = 0{,}324e^{-0{,}19x}$	0,171	$y = 0{,}336e^{-0{,}25x}$	0,312	$y = 0{,}290e^{-0{,}01x}$	0,003
Linear	y = -0,054x + 0,322	0,170	y = -0,074x + 0,333	0,304	y = -0,003x + 0,290	0,003
Logarithmic	y = -0,02ln(x) + 0,274	0,162	y = -0,03ln(x) + 0,269	0,276	n/a	n/a
2nd order polynomial	$y = -0{,}049x^2 + 0{,}001x + 0{,}307$	0,173	$y = -0{,}283x^2 + 0{,}238x + 0{,}251$	0,360	$y = -0{,}260x^2 + 0{,}290x + 0{,}209$	0,050
Power	$y = 0{,}274x^{-0{,}1}$	0,163	$y = 0{,}269x^{-0{,}13}$	0,283	n/a	n/a

5.5.4 Regression analysis for monthly average capacity factor

A regression analysis is performed to investigate the effect of coal calorific content on overall plant efficiency. Results are shown in ***Table 5-6***. Interestingly, all regression curves are decreasing in nature, which coincides with the negative correlation between calorific content and EE.

Table 5-6*: Results of regressions for Plant A EE vs. coal calorific value.*

	Normal		Monthly averaging		Yearly averaging	
	Equation	R^2	**Equation**	R^2	**Equation**	R^2
Exponential	$y = 1{,}902e^{-0{,}09x}$	0,601	$y = 2{,}299e^{-0{,}10x}$	0,665	$y = 0{,}608e^{-0{,}03x}$	0,173
Linear	y = -0,027x + 0,830	0,598	y = -0,030x + 0,889	0,659	y = -0,011x + 0,504	0,175
Logarithmic	y = -0,54ln(x) + 1,901	0,597	y = -0,60ln(x) + 2,081	0,660	y = -0,21ln(x) + 0,931	0,176
2nd order polynomial	$y = -0{,}003x^2 + 0{,}116x - 0{,}584$	0,600	$y = 0{,}006x^2 - 0{,}278x + 3{,}315$	0,664	$y = 0{,}004x^2 - 0{,}201x + 2{,}356$	0,178
Power	$y = 79{,}30x^{-1{,}88}$	0,600	$y = 141{,}1x^{-2{,}08}$	0,666	$y = 2{,}649x^{-0{,}74}$	0,173

5.5.5 Observations for regression analyses

Overall, monthly averaging produced the most accurate results. While the second order polynomial regression consistently produced the best R^2 values, the linear regression is perhaps the best suited when used for M&V baseline adjustment, as it will surely prove the more accurate approximation when datasets are expanded. If higher quality data is used regression analysis results may show more significant R^2 values, and the effect of certain factors on overall plant efficiency may become more clear.

5.6 DEA efficiency tracking

5.6.1 Overview

DEA is now investigated as a plant efficiency tracking method. The process is used in various contexts so as to establish if additional insight can be provided. Besides energy usage/production dataset, additional datasets are incorporated to investigate DEA's potential ability to bring new plant trends to light. DEA's advantages and disadvantages in comparison to classical EE methods are discussed. Its usefulness as both a tool for comparing the efficiency of multiple plants and evaluating a single plant over time is considered. It should be noted that it is very difficult to compare plants of different contexts and technologies. The comparative results for section 5.4 cannot be used as an overall measure of a plant's performance in relation to another, and additional insight is required. DEA is investigated as a means of potentially gaining additional insight into plant performance.

5.6.1 DEA return-to-scale investigation for EE tracking

DEA return-to-scale (RTS) are discussed in section 3.3.6.4. To examine the most suitable RTS orientation for power plant EE tracking, a number of case studies are performed. An EE DEA is performed for each of the case study plants using each of the RTS orientations. The complete results for Plant A, Plant B and Plant C are shown in Appendix B.1 in ***Table B-1, Table B-2*** and ***Table B-3*** respectively. The Root Mean Square Error (RMSE) and correlation between the DEA results and actual normalised EE are calculated and shown in ***Table 5-7***.

Table 5-7: *RMSE and correlations between actual and various RTS orientations DEA.*

Plant A				
	Constant RTS	**Variable RTS**	**Non-increasing RTS**	**Non-decreasing RTS**
RMSE	0,0124	0,0887	0,0427	0,0205
Correlation	97,66%	29,99%	76,42%	94,06%
Plant B				
RMSE	0,0062	0,0162	0,0073	0,0157
Correlation	98,46%	93,94%	97,63%	94,10%
Plant C				
RMSE	0,0353	0,0684	0,0519	0,0569
Correlation	80,62%	47,61%	67,81%	54,48%

Examining ***Table 5-7*** it can be seen that the constant RTS orientation consistently performs the best of the various DEA orientations, with the highest correlation scores and lowest RMSE values. However, this is because the process whereby the normalised efficiency is calculated and normalised is inherently linear in nature and thus comparable to a constant return to scale, so DEA results will be similar in nature. When DEA is used in an EE context, the constant RTS will thus produce the most accurate results, as we are interested in both the scale and technical efficiency. When mass and calorific values are used the analysis is similar in nature (however more degrees of freedom are incorporated with the extra input categories) and the evaluation of plant EE is still the primary target. Thus constant RTS is also used in these analyses.

5.6.2 DEA EE analysis

DEA's use in energy efficiency tracking is now evaluated. The energy efficiency tracking study now repeated using the DEA software application. The dataset used in this analysis is shown in ***Table 5-8***.

Table 5-8*: Inputs and outputs used in results of DEA EE analysis between plants.*

Inputs	**Outputs**
Monthly total energy content of coal consumed [GJ]	Total electrical energy sent out [MJ]
Monthly total energy content of secondary fuel consumed/ auxiliary plant power consumed [MJ]	

Plant A, B and C are evaluated over a 2 year period, from 2012 to 2013. Results are shown in ***Table 5-9***. The constant RTS DEA orientation is selected for use. Energy efficiency analysis results are also shown, normalised by the value of the most efficient plant to allow efficiencies to be compared.

Table 5-9*: DEA energy efficiency plant comparison results.*

Plant	**DEA efficiency**	**Normalised energy efficiency**
Plant A	88,97%	87,54%
Plant B	94,02%	93,77%
Plant C	100%	100%

DEA identified Plant C as the most efficient, with Plant B second and Plant A third. These results are very close to normalised actual EE results. The small difference may be due to rounding error or estimation methods employed by the linear programming algorithm utilised by the software application when performing DEA.

To compare the plants on a month to month basis, each plant is analysed individually. Their results are then scaled by their overall efficiencies as calculated in ***Table 5-9***, so as to make accurate comparisons. Results are shown in Appendix B.1 in Table B-5 and represented visually in ***Figure 5-8***.

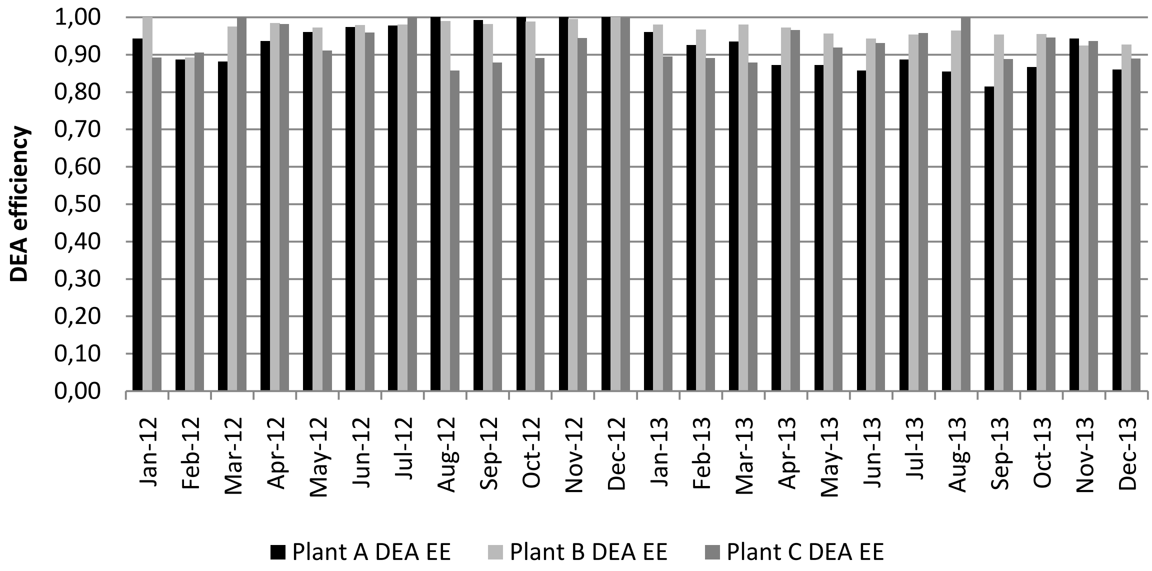


Figure 5-8*: Scaled monthly DEA energy efficiency plant comparison results.*

It can be seen that the DEA EE results are very similar to the EE results, with almost identical trending in efficiency. Plant A shows a 97,66% correlation between DEA EE and classical EE values, while Plant B shows a 98,46% correlation. Plant C's results show slightly weaker correlation at 80,62%. Plant C is a more modern plant and thus is expected to perform the best of the three plants. Plant A and B are of similar vintage and have a similar MW rating, however Plant B performs significantly better. As discussed previously in section 5.4, this higher efficiency value may be due to a number of factors, such as climatic conditions, fuel calorific values, the capacity factor at which the plants operate and plant operational and maintenance procedures. The effects of these factors are now investigated using DEA.

5.6.3 DEA efficiency tracking using fuel mass and calorific content

DEA is now applied to a second case study. This analysis attempts to evaluate the case study plants without using total energy input or energy input per fuel source. The mass of fuel used is considered instead, as well as the associated fuel calorific content.

5.6.3.1 DEA efficiency tracking using fuel mass and calorific content between multiple plants

The effect of fuel mass and calorific values is investigated by evaluating plants comparatively. The datasets used in this analysis is shown in ***Table 5-10***.

Table 5-10*: Inputs and outputs used in DEA EE analysis between plants with fuel mass and calorific content.*

Inputs	Outputs
Monthly total mass of coal consumed [tons]	Total electrical energy sent out [MJ]
	Average monthly calorific content of coal consumed

	[MJ/kg]

As Plant C uses a different secondary fuel (in the form of natural gas), this dataset is omitted from this analysis. Processing low-quality coal requires more auxiliary plant energy and may thus affect efficiency. The above inputs may thus allow insight into this effect. The calorific values are treated as outputs as a higher calorific value is desired and the DEA methodology attempts to minimise inputs. DEA identifies Plant A as inefficient, with a rating of 88,88%. However, both Plant B and Plant C are considered efficient. It can thus be concluded that Plant B and Plant C utilise their fuel supplies more effectively. The average calorific content for each plant is shown in ***Table 5-11***.

Table 5-11*: Average calorific content of coal for case study plants.*

Plant A	**Plant B**	**Plant C**
19,51 MJ/kg	20,19 MJ/kg	20,42 MJ/kg

Table 5-11 shows that Plant A's average calorific content is significantly lower than both Plant B and Plant C. Thus, Plant A must process larger quantities of fuel when compared to both Plant B and Plant C.

5.6.3.2 DEA efficiency tracking using fuel mass and calorific content for individual plants

A DEA fuel mass and calorific content analysis in now performed on the three case study plants. All three analyses consider the mass and average calorific content of coal, as well as the total sent out electrical energy. Plant A and Plant B's analysis both consider the mass and average calorific value of fuel oil consumed, while Plant C's considers the volume and average calorific content of natural gas consumed. Plant A's analysis incorporates the auxiliary plant electrical energy consumed (this dataset is unavailable for Plant B and Plant C). The DEA results of all three analyses are shown in Appendix B.3 in Table B-6. To evaluate difference between mass/calorific value and EE results, correlation and RMSE is used. These results are shown in Table 5-12.

Table 5-12*: RMSE and correlation between EE and mass/calorific value DEA results*

	Plant A	**Plant B**	**Plant C**
RMSE	0,0442	0,0259	0,0352
Correlation	84,34%	57,96%	76,12%

All three case study plants have a relatively small RMSE value. This coupled to the moderate-to-strong results of the correlation show that the mass/calorific value DEA analysis produces similar results to the EE DEA, highlighting similar trends in plant efficiency. Each case study plant's results are shown visually in ***Figure 5-9*** to ***Figure 5-11***.

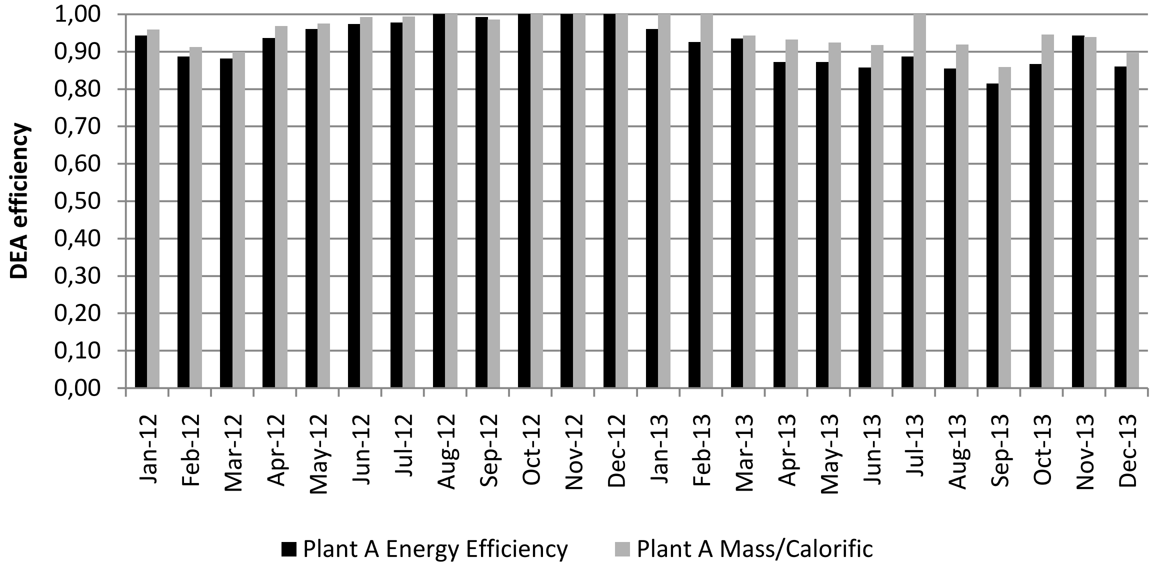


Figure 5-9*: EE vs. mass/calorific DEA results for Plant A.*

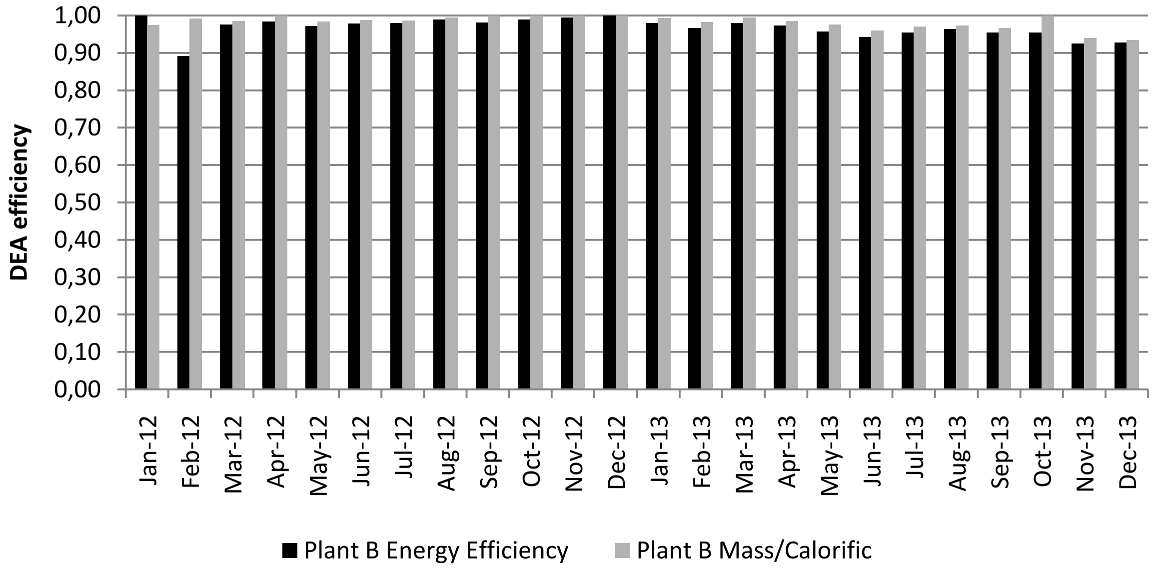


Figure 5-10*: EE vs. mass/calorific DEA results for Plant B.*

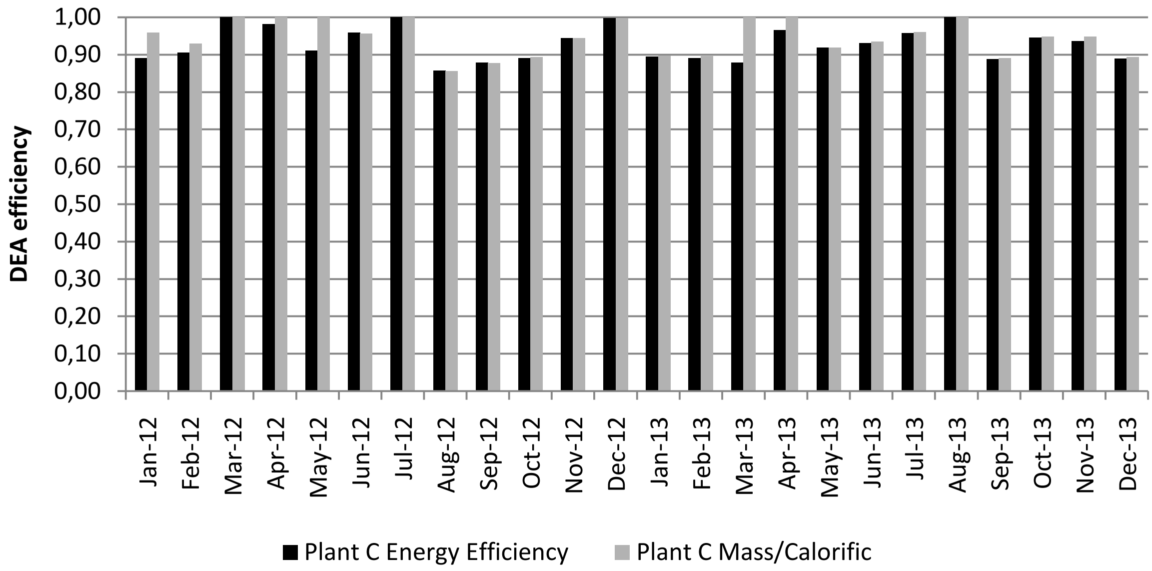


Figure 5-11: *EE vs. mass/calorific DEA results for Plant C.*

Examining ***Figure 5-9*** to ***Figure 5-11***, it can be seen that the mass/calorific content DEA consistently shows higher efficiencies than the EE DEA results. Additional efficient months are identified by the mass/calorific analysis, which were not deemed efficient by the EE analysis. For Plant A these months are January, February and July 2012. For Plant B these months are September and November 2012 as well as October 2013 while for Plant C these months are April and May 2012 and March and April 2013. These months may have made use of less fuel with a higher average calorific value. Plant B and Plant C's calorific value data showed very little fluctuation (almost 0% for secondary fuels). These advantages could not be highlighted using and EE or DEA EE analysis. This could be evidence of averaging in fuel calorific content data, which brings into question the fidelity of this data.

5.6.4 DEA efficiency tracking with climate factors

To examine the effects of climatic conditions on plant efficiency, the DEA energy efficiency of each case study plant is compared to climate data, consisting of each plant's average monthly maximum temperature and total monthly rainfall. Climate data for all three case study plants is shown in Appendix B.4 in ***Table B-7***. The correlation between DEA energy efficiency and average monthly maximum temperature as well as between DEA energy efficiency and total monthly rainfall is shown in ***Table 5-13***.

Table 5-13: *Correlations between DEA energy efficiency and climate factors.*

	Plant A	**Plant B**	**Plant C**
Correlation with temperature	0,0381	-0,1679	0,2534
Correlation with rainfall	0,59%	-8,93%	37,47%

As covered in section 2.2.5, higher temperature and higher rainfall are associated with a decrease in plant performance. However, ***Table 5-13*** shows no conclusive evidence of this negative correlation. Coal stockpiles and bunkers act as coal supply "buffers" and mean that rainfall may not immediately effect coal moisture content and thus efficiency.

The available dataset includes average monthly consumed coal moisture content for Plant A for the 2012 year. Thus, an energy efficiency DEA is performed using only plant A's data for the 2012. This analysis includes the same inputs as used in section 5.5. Both Plant A's DEA EE for 2012 and coal moisture content are shown in Appendix B.4 in ***Table B-8***. A -52,28% correlation is present between these dataset, evidence of a moderate negative correlation between plant efficiency and coal moisture content. This correlation in conjunction with the lack of a correlation between rainfall and plant efficiency may show the effect of plant coal stock piles and bunkers i.e. there may be a delayed effect between rainfall and a decrease in plant efficiency due to a higher moisture content. A weak correlation of 31,85% between Plant A's rainfall and consumed coal average moisture content seems to support this.

For further insight into the effect of coal moisture content a DEA analysis is now performed incorporating coal moisture content as an input. The datasets used in this analysis are shown in ***Table 5-10***.

Table 5-14*: Inputs and outputs used in DEA EE analysis for Plant utilising coal moisture content data.*

Inputs	**Outputs**
Average monthly moisture content of coal consumed [%]	Total electrical energy sent out [MJ]
Monthly total mass of coal consumed [tons]	
Monthly total mass of fuel oil consumed [kg]	
Auxiliary plant energy consumed [MJ]	

The analysis was performed on a monthly basis during 2012. Mass values were selected as additional inputs as the unit of coal moisture content is a percentage of mass. The analysis is repeated but coal moisture content data is excluded. Results are shown in Appendix B.4 in ***Table B-9***. Results are represented visually in ***Figure 5-12***.

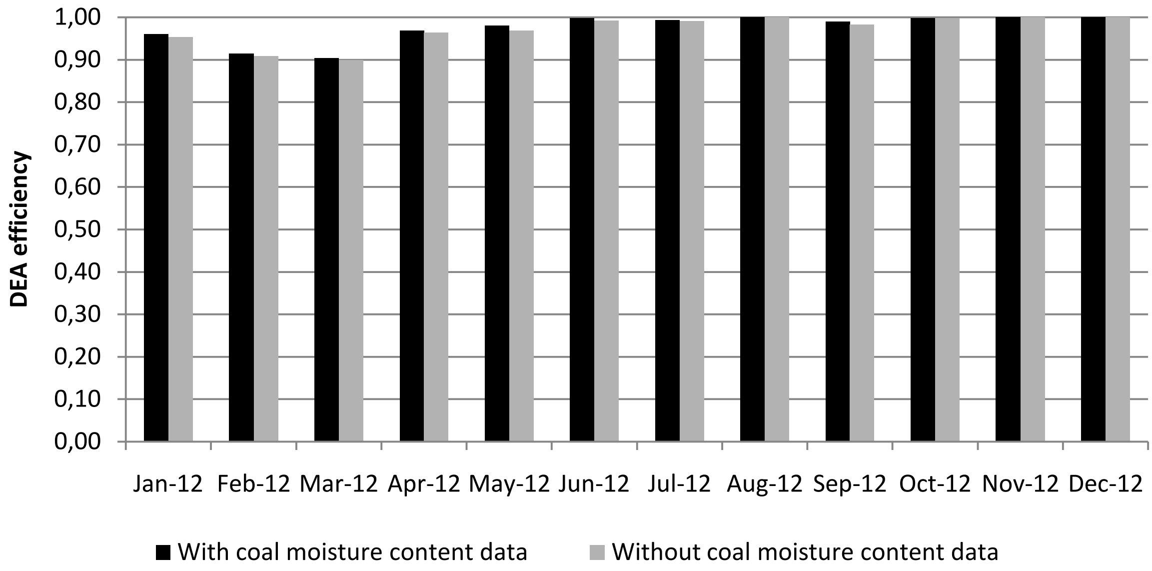


***Figure 5-12**: DEA mass analysis for Plant A including coal moisture content.*

Comparing results for the mass analysis with and without coal moisture content data, it is visible that results are very similar and the same efficient months are identified in both cases. A number of the inefficient months score slightly higher when coal moisture content data is included. In these cases coal moisture content is slightly lower and will results in a higher EE. The small difference in efficiencies between the two result sets can be attribute to the small variation in calorific content, with a maximum variation of 1,63%.

5.6.5 DEA efficiency tracking with capacity factor

The capacity factor at which a plant operates has an effect on its overall efficiency, as described in section 2.2.5. To establish the extent of this effect the correlation between capacity factor and EE for each of the case study plants. Monthly average capacity factor for each case study plant is shown in Appendix B.5 in ***Table B-10***. Plant B and Plant C show inconclusive correlations at 7,04% and -13,57% respectively. Plant A shows a weak-to-moderate correlation of -41,26%. It can thus be concluded that Plant B and Plant C are designed to operate as effectively at a lower capacity factor as at a higher capacity factor.

To further investigate the effects of capacity factor on plant efficiency, a DEA is performed on Plant A using the following parameters:

***Table 5-15**: Inputs and outputs used in DEA EE analysis for Plant utilising capacity factor data*

Inputs	**Outputs**
Monthly total mass of coal consumed [tons]	Monthly average capacity factor [%]
Monthly total mass of fuel oil consumed [kg]	

Fuel mass is used as this investigation attempts to remove the capacity factor value from energy values while still investigating its usefulness in a DEA context. A higher capacity factor is valued, and therefore this data is treated as an output. Results from this analysis are shown in Appendix B.5 in ***Table B-11***. Results are shown visually in ***Table 5-13***.

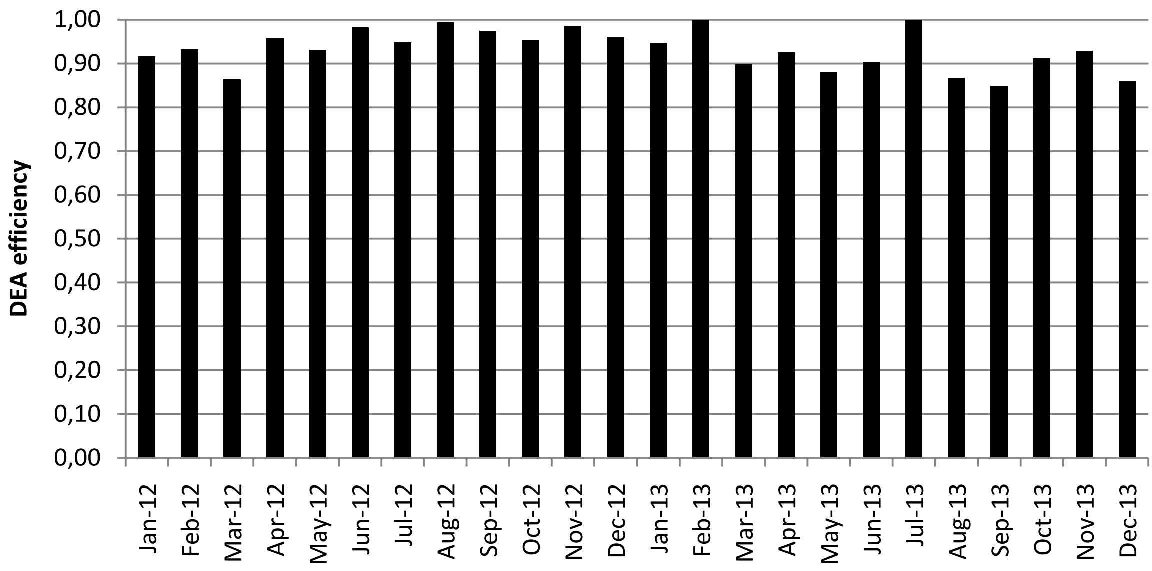


Figure 5-13*: DEA results including monthly average capacity factor for Plant A.*

February and July 2013 are identified as the efficient months in this analysis. Neither of these two months are identified as efficient in the EE DEA, however both appear efficient in the fuel mass and calorific value analysis. The capacity factor may provide insight into the extent to which plant facilities are being utilised, but offer little in the way of EE insight.

5.6.6 DEA eco-efficiency tracking

In this section DEA is used to evaluate the eco-efficiency of the case study plants, both individually and comparatively. The available dataset includes the average monthly ash and sulphur content of coal consumed by all three case study plants. Ash and sulphur are both considered pollutants, which negatively affect the plants' surrounding environments and human health. The eco-efficiency is defined as the amount of ash and sulphur consumed by the for the electrical energy released. The total energy input is included as an input so as to gauge the environmental "cost" of plant energy efficiency. For the comparative eco efficiency DEA, inputs and outputs are shown in ***Table 5-16***. Results are shown in ***Table 5-17***.

Table 5-16*: Inputs and outputs used in comparative DEA eco-efficiency analysis*

Inputs	**Outputs**
Monthly total energy input [MJ]	Monthly total sent out electrical energy [MJ]

Monthly average ash content of fuel [%]	
Monthly average sulphur content of fuel [%]	

***Table 5-17**: Results of comparative eco-efficiency DEA.*

Plant A	Plant B	Plant C
89,23%	100%	100%

The DEA process fails to differentiate between the eco-efficiency of Plant B and Plant C, however, Plant A under-performs in relation to both these plants. Examining the datasets it is easy to see why, as Plant A's ash and sulphur content is far higher than that of either of the US plant. Plant A's eco-efficiency is now tracked on a monthly basis for the 2012 calendar year using the same datasets as in ***Table 5-16***. Monthly eco-efficiency results are shown in Appendix B.6 in ***Table B-12*** and visually in ***Figure 5-14***. Results are compared to DEA EE results.

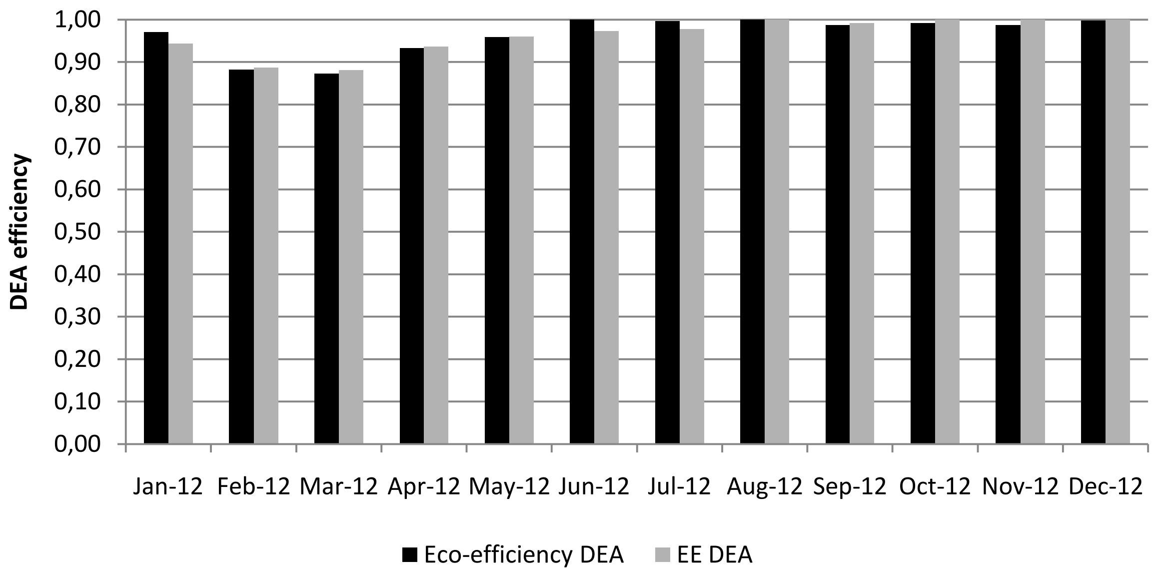


***Figure 5-14:** DEA eco-efficiency and EE for Plant A.*

The DEA eco-efficiency results identified certain months as more or less efficiency than DEA EE results. Months such as January, June and July performed well despite a lower emission "cost", while months like February, March, April, September, October and November had higher emissions for their achieved performance. DEA can thus easily benchmark the eco-performance of a plant.

5.6.7 DEA efficiency tracking with monthly averaging

5.6.7.1 Overview

The datasets used for the case study plants usually only measure coal sent to the plant bunker, rather than coal sent to the boiler. As such a "lag" is caused, which may affect the accuracy of results. In this section the case study plants are examined using DEA with monthly averaging. Each dataset is averaged on a three month basis i.e. previous, current and following month's data is considered. This method of averaging attempts to minimise the lag in coal data. This method is applied to an EE analysis as well as a DEA EE, mass/calorific and mass/moisture content analysis for Plant A.

5.6.7.2 DEA EE analysis with monthly averaging

An EE and EE DEA analysis are performed for Plant A and Plant B using the moving average data. Results for both analyses are shown in Appendix C.1 in ***Table C-1*** for Plant A and in ***Table C-2*** for Plant B. These results are shown visually in ***Figure 5-15*** and ***Figure 5-16*** for Plant A and Plant B respectively.

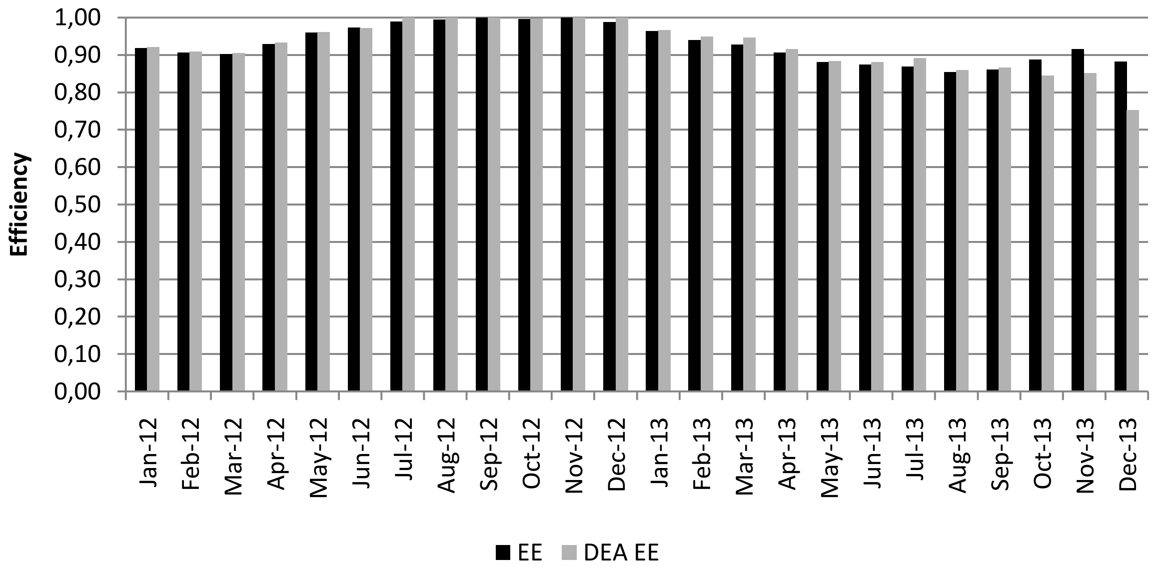


Figure 5-15*: Results of EE and EE DEA for Plant A with monthly averaging.*

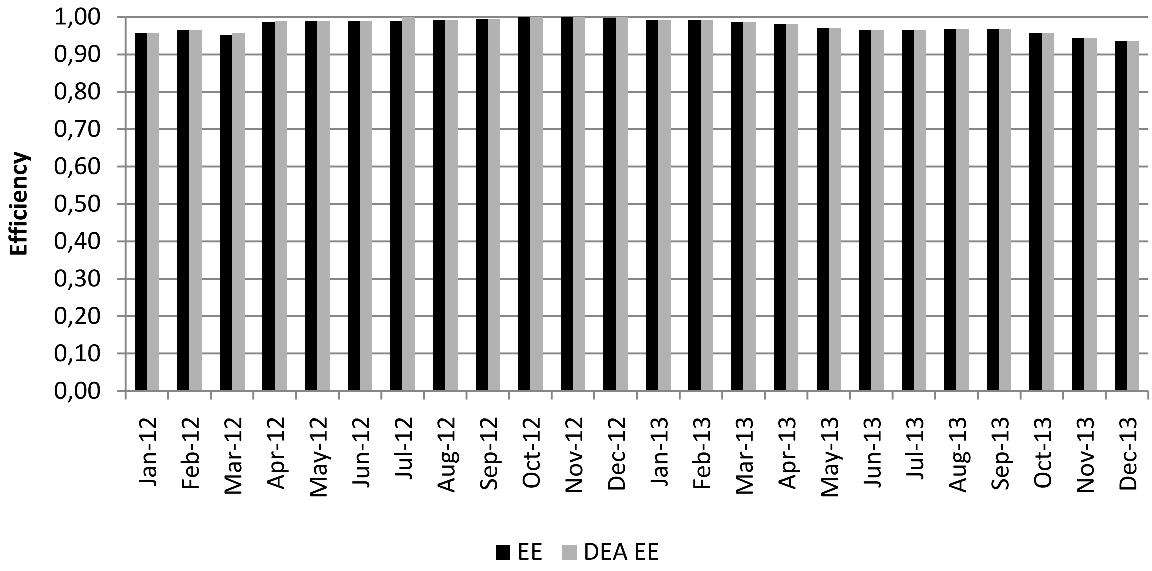


***Figure 5-16**: Results of EE and EE DEA for Plant B with monthly averaging.*

For Plant A an RMSE of 0,03198 and correlation of 87,18% show that results are very closely related. Plant B has similarly strong results with an RMSE of 0,0024 and a correlation of 99,28%. In ***Figure 5-17*** the results of the EE DEA with and without 3 month averaging are compared for Plant A. Examining the results for Plant A, there is little to no extra information. Plant B shows a slightly higher average efficiency during the colder winter months. However, the region received unseasonably high rainfall during the later months of 2013, which shows in the sharp decrease in efficiency during these months.

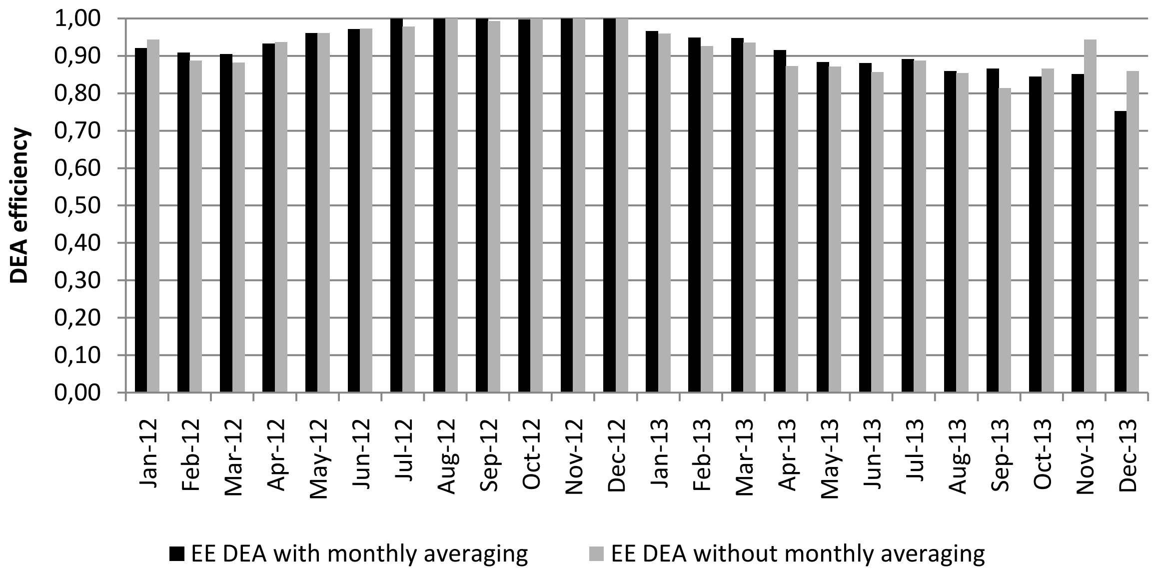


***Figure 5-17**: EE DEA with and without three month moving average for Plant A.*

Figure 5-18 similarly compares the EE DEA results with and without averaging for Plant B. Trends are similar, with only significant differences in January and February 2012.

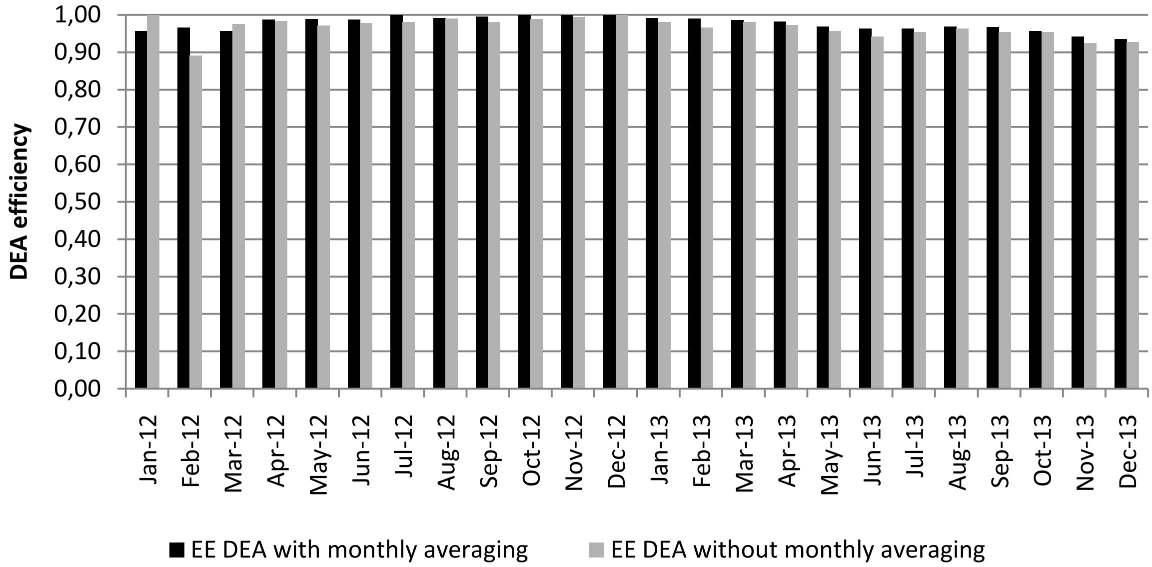


Figure 5-18*: EE DEA with and without three month moving average for Plant B.*

5.6.7.3 DEA efficiency tracking for Plant A with coal moisture and monthly averaging

Coal moisture content theoretically has an adverse effect on overall plant efficiency. When investigated in section 5.6.4 a weak to moderate correlation was identified between coal moisture content and plant efficiency. However, these results were most likely affected by the coal bunker "lag" mentioned before. If the correlation between monthly average coal moisture content and EE with moving three month average is taken it shows a moderate-to-strong negative correlation at -58,23%. This result prompts further investigation using DEA. A DEA is performed using the following three month moving average datasets:

Table 5-18*: Inputs and outputs used in DEA EE analysis for Plant utilising coal moisture content data*

Inputs	**Outputs**
Average monthly moisture content of coal consumed [%]	Total electrical energy sent out [MJ]
Monthly total mass of coal consumed [tons]	
Monthly total mass of fuel oil consumed [kg]	
Auxiliary plant energy consumed [MJ]	

As before, the analysis is performed on a monthly basis. However, as the coal moisture content dataset only covers the year of 2012, the analysis is only performed over these 12 months. Results are shown in Appendix C.1 in ***Table C-3*** and shown visually in Figure 5-19. Results are compared to three month moving average EE results.

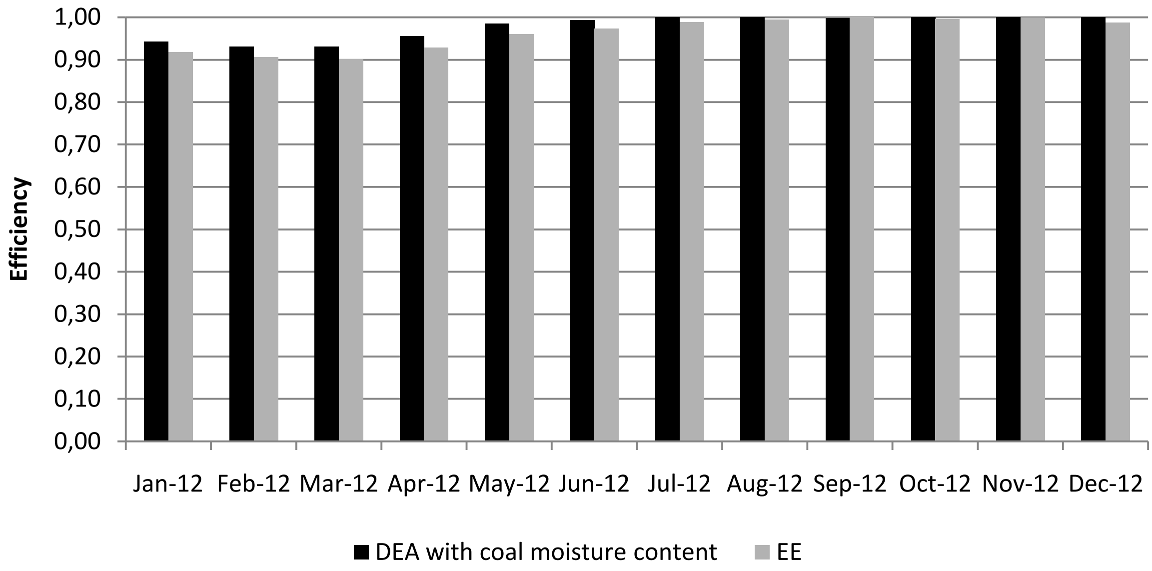


***Figure 5-19**: Results of DEA with coal moisture content three month moving average and EE with three month moving average for Plant A*

As is visible in ***Figure 5-19*** the coal moisture results consistently score higher than the normalised EE results. This may be due to the small variation in coal moisture over the 12 months. This analysis thus fails to highlight any new inefficiencies brought about by coal moisture. The previously-mentioned coal bunker effect may require a larger time averaging window to bring a correlation with plant efficiency to light.

5.6.7.4 DEA efficiency tracking using fuel mass and calorific content with moving average

As before the correlation between plant efficiency and mass of fuel is examined, this time using the three month moving average datasets. For Plant A, coal's mass data has a moderate-to-strong negative 66,58% correlation with plant EE, while fuel oil data has a weak-to-moderate correlation of negative 40,78%. Plant efficiency thus decreases with higher physical quantities of fuel, as the handling and preparation process of this fuel draw larger amounts of auxiliary energy. For attempted further insight into this effect, a DEA is performed incorporating the datasets shown in ***Table 5-19*** (all in their moving average form).

***Table 5-19**: Inputs and outputs used in DEA EE analysis for Plant B with fuel mass and calorific content and monthly averaging.*

Inputs	**Outputs**
Monthly total mass of coal consumed [tons]	Total electrical energy sent out [MJ]
Monthly total mass of fuel oil consumed [kg]	Average monthly calorific content of coal consumed [MJ/kg]
	Average monthly calorific content of fuel oil consumed [MJ/kg]

Results are shown in Appendix C.1 and visually in ***Figure 5-20***. Also shown in are results for the similar analysis from section 5.6.3 which does not use a three month moving average.

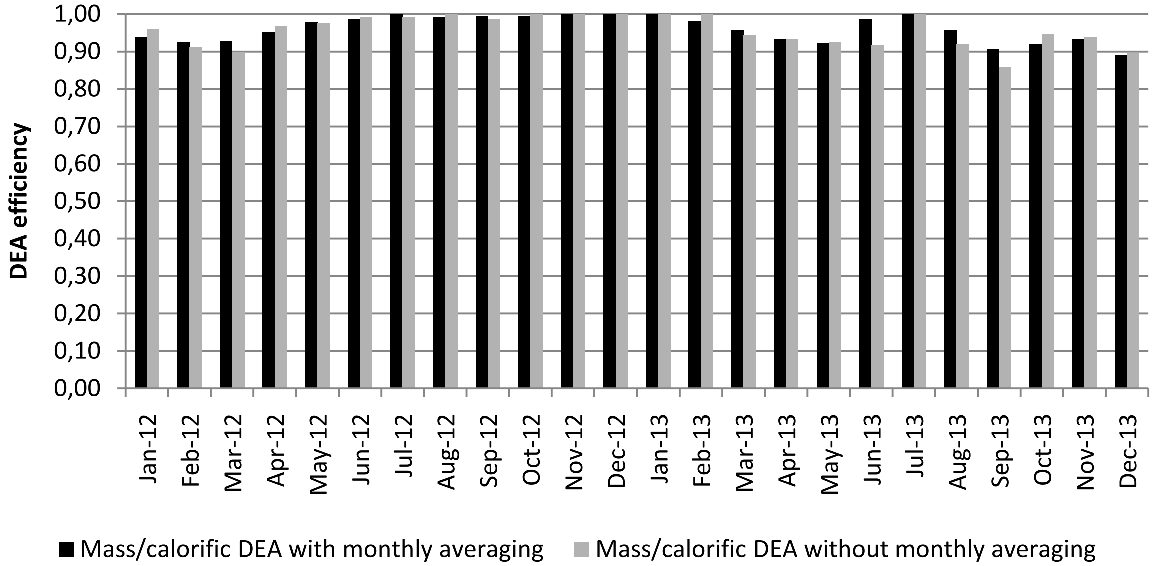


Figure 5-20*: Results of fuel Mass/calorific value DEA for Plant A with and without three month moving average.*

Figure 5-20 shows that the results of the moving average analysis and the normal analysis show the same trends and little in the way of deviation from each other. The only significantly different period is June 2013, which was identified as almost 7% more efficient when the moving average dataset was considered. As the moving average analysis does not highlight any additional trends these new results are of little value.

5.6.7.5 DEA eco-efficiency tracking with monthly averaging

The eco-efficiency of Plant A is now investigated using monthly averaging. Ash and sulphur content of the consumed coal are considered. As this data is measured before coal is sent to the bunker (as with calorific content), monthly averaging may produce more accurate results. ***Table 5-21*** shows the inputs and outputs used in this analysis. Results are shown in Appendix C.1 in ***Table C-5*** and visually in ***Figure 5-21***.

Table 5-20*: Inputs and outputs used in comparative DEA eco-efficiency analysis*

Inputs	**Outputs**
Monthly total energy input [MJ]	Monthly total sent out electrical energy [MJ]
Monthly average ash content of fuel [%]	
Monthly average sulphur content of fuel [%]	

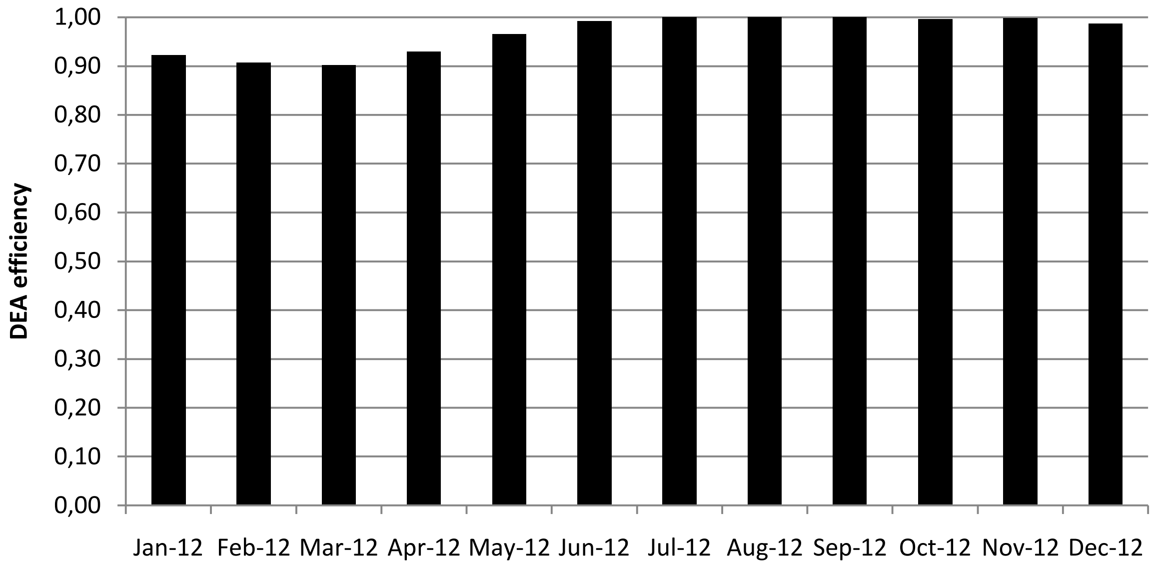


Figure 5-21*: Eco-efficiency DEA results for Plant A with monthly averaging.*

Figure 5-21 shows that the plant's eco efficiency was significantly lower during the first five months of 2012. Some of the interventions performed during these first few months included coal quality analysers, which may have led to a decrease in the average consumed coal ash and sulphur content. A more simple explanation may be that plant EE increased during these later months, which led to less fuel consumed per MJ produced and thus less ash and sulphur per MJ produced.

5.6.8 DEA efficiency tracking with calendar year averaging

5.6.8.1 Overview DEA efficiency tracking with calendar year averaging

For further investigation into DEA's use as an efficiency tracking tool in power plant contexts, yearly averaging of historical data is now considered. The analyses are thus performed in a similar manner as before but using the historical data for 2 calendar years.

5.6.8.2 DEA EE tracking over two year period yearly average

All three case study plants' actual efficiencies are evaluated using two year yearly average data for monthly intervals in section 5.4.5. Plant C performs the best, with an average efficiency of 33,35% while Plant B and Plant A score 31,32% and 28,84% respectively (these results agree with those from section 5.4.2 as they consider the same datasets).

An EE DEA is now performed on each plant. Results are shown in Appendix D.1 in ***Table D-1***. These results are also shown visually in ***Figure 5-22*** (Note: these results are not scaled to each other and are simply shown on the same set of axes). ***Table 5-21*** shows the correlation and RMSE values for these results with EE results from section 5.4. Once again, all three RMSE values are low and correlation values are high.

***Table 5-21**: Correlation and RMSE between EE DEA and EE results for two year yearly average datasets.*

	Plant A	Plant B	Plant C
RMSE	0,0163	0,0150	0,0049
Correlation	87,71%	78,28%	98,62%

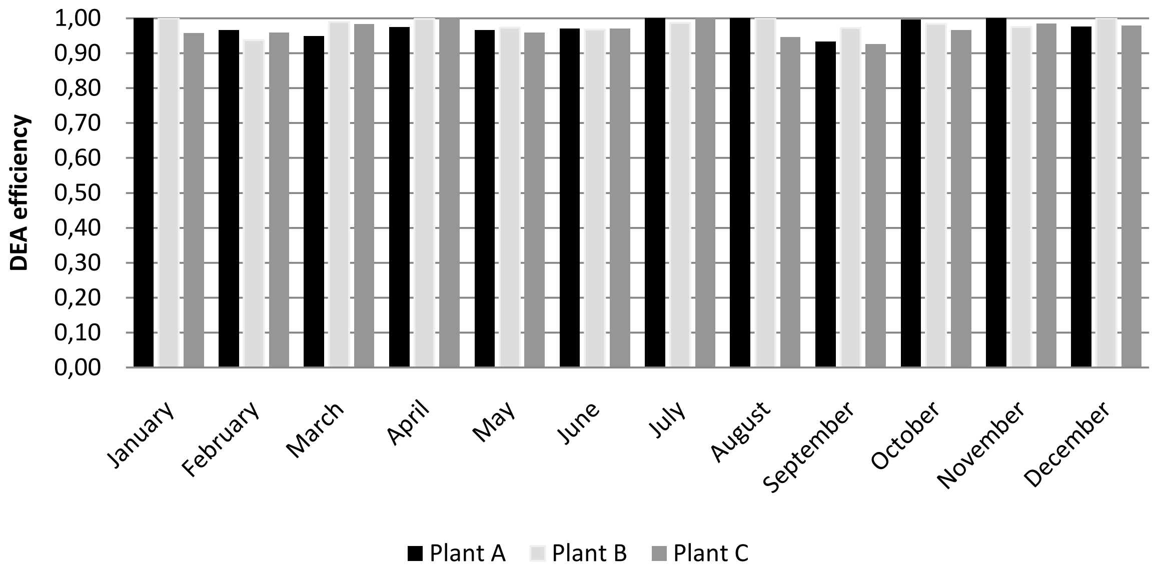


***Figure 5-22**: EE DEA results for case study plants with two year yearly average data.*

5.6.8.3 DEA fuel mass and calorific content EE tracking over two year period yearly average

The EE of Plant A is now examined using datasets with calendar year averaging and fuel mass and calorific values. The datasets used in this analysis are shown in ***Table 5-22***.

***Table 5-22**: Inputs and outputs used in DEA EE analysis for Plant A with fuel mass and calorific content and two year averaging.*

Inputs	Outputs
Monthly total mass of coal consumed [tons]	Total electrical energy sent out [MJ]
Monthly total mass of fuel oil consumed [kg]	Average monthly calorific content of coal consumed [MJ/kg]
Monthly total auxiliary electrical energy consumed [MJ]	Average monthly calorific content of fuel oil consumed [MJ/kg]

Results are shown in Appendix D.1 in ***Table D-1*** and visually in ***Figure 5-23***. Plant A now showed more significant correlations with climate data, at -46,89% with temperature and -87,50% with monthly rainfall. Thus, it may be concluded that averaging over multiple calendar years helps identify seasonal trends in plant efficiency. There is no significant correlation between efficiency and coal moisture content though, as the moisture content dataset only covers 2012 and does not consider 2013's data. When a DEA is performed that takes fuel mass into account rather than fuel energy content, the effect of climatic variations on plant efficiency becomes more clear. As calorific content does not show radical fluctuations, and the quality of measured data is questionable, a mass-based analysis may produce more accurate results, especially when multiple datasets are averaged.

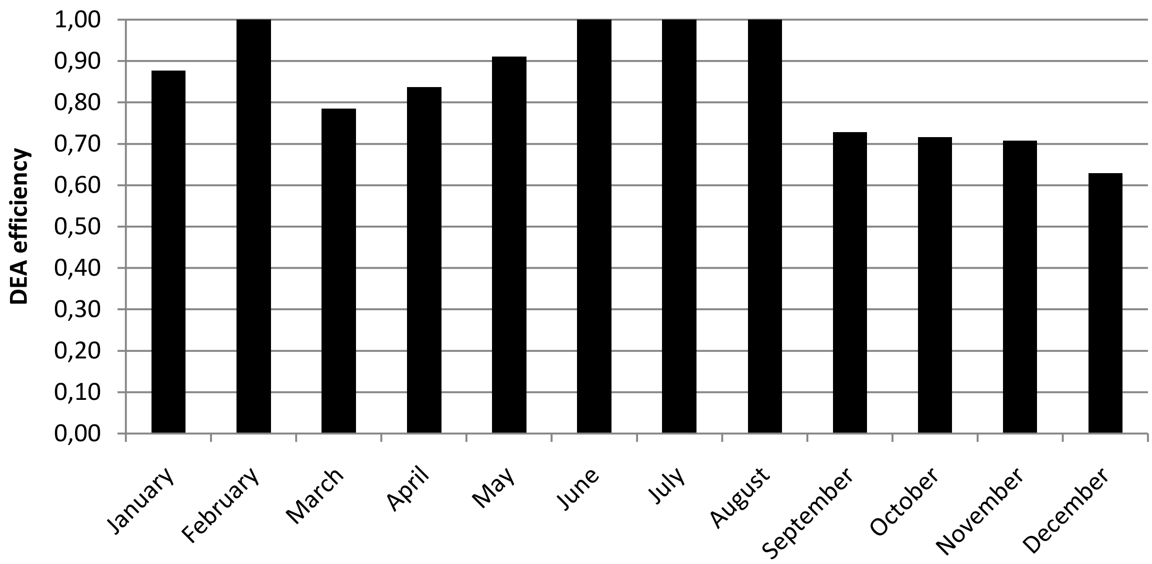


***Figure 5-23**: Fuel mass and calorific value DEA results for Plant A with two year yearly average data.*

5.6.9 Observations for DEA efficiency tracking

DEA provides a convenient overview of plant performance, both over time and in relation to other plants. However, when subjected to the same datasets as a conventional EE analysis, no new information is produced. While DEA can easily incorporate additional factors, such as climate data (e.g. temperature, rainfall) and operational data (e.g. capacity factor) to produce results, the effect of these factors on overall plant efficiency is not always clear. Averaging holds a limited potential to help bring trends to light. In the case of this project, averaging helps to minimise the effect of the coal bunker. The data used in this project is typically of fairly low quality, especially for Plant A. The accuracy of DEA results is very largely dependent on data accuracy. In this project plants are evaluated overall, utilising the minimum number of inputs and outputs. To gain insight into plant performance DEA should ideally be performed on individual plant components (such as boiler, turbine etc) using intermediate inputs and outputs.

6 Conclusions and recommendations

6.1 Overview of conclusions and recommendations

With global declines in availability of traditional fossil fuels as well as constraints on South Africa's national energy grid, Energy Efficiency (EE) efforts have become increasingly relevant and necessary [1, 2]. Although the worldwide installed capacity of renewable energy technologies has seen a dramatic increase, thermal power stations still generate the majority of global electrical energy [17]. As such, the accurate tracking of power station efficiency is vital in EE projects. However, traditional methods of efficiency tracking are often cumbersome, expensive and produce ambiguous results [25].

Measurement and Verification (M&V) is the term given to the process whereby the savings of an EE intervention are determined [6]. M&V evaluates the pre-implementation energy usage of a project by constructing a baseline, consisting of measured historical data. External changes may require this baseline to be adjusted for higher accuracy, but this process can often be too rigid and may not consider the project's unique conditions [5].

Data envelopment analysis, a non-parametric linear benchmarking technique [14], may serve as a novel diagnostic tool for evaluating the relative efficiency of multiple plants, as well as monitoring the efficiency of a single plant over time. The non-parametric natures allows for the inclusion of multiple factors and may allow for insight into their effect on overall plant efficiency. This project thus aims to answer the following questions:

- How well do classical methods serve in the evaluation and tracking of power plant efficiency?
- How well suited are classical methods to the comparative benchmarking of power plants?
- Can regression analysis be used to determine the extent to which plant performance is affected by external factors?
- Can the results of regression analysis be used in an M&V context for baseline adjustment purposes?
- How well can DEA be employed as a diagnostic tool in power plant efficiency monitoring and comparative benchmarking?
    - To what extent can DEA results be used to identify both presence and nature of plant inefficiencies?

- What choice of input and output datasets produces the most accurate and/or useful results?
- Can the effect of both environmental and operating variations be evaluated using DEA results?
- Can the accuracy of DEA results be improved/made more useful when time averaging is employed?
- Is it possible for DEA to provide additional insight into plant performance that may not be covered by classical efficiency evaluation methods?

The literature study discusses important topics relevant to the development and implementation of a plant efficiency analysis software application. This included software development as well as relational database concepts. The literature study also covers the basic operations of thermal plants, and the factors that may affect plant performance. Statistical methods used in model validation are also addressed. Classical efficiency evaluation methods and the DEA process are covered in depth in a separate section. A target plant is analysed as test case during the case studies.

This project consists of the implementation of classical efficiency evaluation methodologies, as well as the development of a DEA methodology with the view of power plant performance assessment, and an associated software application. This is done by accomplishing the following objectives:

- *Develop a relational database*: A relational database is successfully developed and implemented to allow for the storage of historical plant data and is designed for its easy retrieval.
- *Develop a software application*: An application is developed that allows for classical efficiency evaluation and DEA-based data analysis. This application includes a user-friendly GUI and backend database support.
- *Determine the extent to which classical efficiency evaluation methods can be used to track plant efficiency as well as benchmark plant performance in terms of other plants*: These methods are well suited to determining actual efficiency of the plant. Although plants can be compared directly, classical methods can't account for differences in plant design and operation, as well as operating conditions.
- *Determine the extent to which classical efficiency evaluation methods can be used to identify the effects of additional environmental and operational factors on overall plant efficiency:* Correlations between efficiency and external factor datasets may be examined, it is difficult to incorporate these factors into the overall rating of the plant.

- *Determine the usefulness of regression analysis when used in a power plant efficiency evaluation and M&V context:* Regression provides further insight into the effect of external factors on plant efficiency. The equations produced as results can be used in M&V for more accurate baseline adjustments.
- *Determine the usefulness of DEA as a diagnostic tool to track plant efficiency and performance in various contexts*: DEA is found to have the potential to provide valuable data when used with energy efficiency data in conjunction with additional factors.
- *Determine if DEA results can be used to identify the presence and nature of inefficiencies*: DEA was found to easily highlight periods with decreased performance. Additional scrutiny of plant data for these periods was required to identify the sources of these inefficiencies.
- *Determine if the accuracy of results could be increased by considering time averaged data*: Data with a moving time average was found to produce more accurate results and provide more useful insight than yearly average data.
- *Determine the quality of data necessary to produce accurate DEA results*: Plants with lower fidelity data were identified and the effect of various data measuring procedures discussed.
- *Conduct relevant case studies to accomplish the preceding objectives*: numerous case studies were performed for both DEA efficiency tracking and baseline formulation using various plants, inputs, outputs and orientations.

6.2 Conclusions and recommendations

6.2.1 Design and development

6.2.1.1 Relational database development

A unique relational database is developed to store historical plant data and metadata. The database was designed to be easily repurposed, observing the Codd's normalisation guidelines. The implemented relational database successfully stores historical plant data by profiles per plant and unit. This structure allows the database to be quickly and effectively queried by external users and software applications, making the retrieval of plant data straightforward. The database is successfully hosted on *WAMPServer* 2.2.

6.2.1.2 Software application development

The implemented software application serves to perform the necessary DEA-based operations. The following necessary prerequisites for the application were successfully achieved:

- *Connect to database of user's choice:* A database connector is implemented to easily create a database connection for use by a software application. Historical plant data can thus be queried, altered and stored.
- *Implement classical efficiency evaluation methods:* actual, technical and scale efficiency, as well as heat rate methods are incorporated. These are utilised in the analysis of historical plant datasets.
- *Implement DEA on plant data using various models and RTS orientations:* DEA is performed by using an external dynamic link library (DLL) for linear programming problems. The user selects the plant(s) considered in the analysis as the input and output category data to be used. The DEA model and RTS orientation, as well as the time window are also selected for the analysis.
- *Export results to Excel for easy viewing and analysis by the user:* An export function is added to insert all results into a an *Excel* worksheet. The user is then free to alter and save the results as desired.
- *Implementation of a graphical user interface (GUI):* A GUI is implemented for each form, giving the user access to all the software application features.
- *Implement a portable and re-usable software design:* The modular nature of the application's architecture allows for future expansions, as well as being efficient for testing purposes.

6.2.2 Case study and analysis conclusions and recommendations

This section presents the conclusions and recommendations for each of the methodologies investigated, including classical efficiency evaluation methods, regression analysis and DEA efficiency evaluation, as well as the RTS orientations used in DEA efficiency evaluation.

6.2.2.1 Classical efficiency evaluation conclusions and recommendations

Actual efficiency, the ratio of energy output to energy input, is the most common expression of EE performance. Heat rate is another measure of efficiency, and is often used to express plant performance. The process, though easily calculated, is very dependent on accurate data measurement. Plant energy intake must be very accurately measured, both in terms of fuel mass and energy content, to produce meaningful results. When the target plant is evaluated on a daily basis data outliers frequently arise. This is mostly due to sampling error, as these data points often show unattainable plant performance levels. This is evidence of inaccurate measurement of either fuel mass, energy content, auxiliary energy usage or sent out electrical energy. For more accurate results, data should be verified. A higher sampling frequency may also have a positive impact on the accuracy of results. By examining unit up-time in conjunction with overall plant efficiency the more and less efficient units can be identified. The target plant has wet cooling on four of its units, and dry cooling on the remaining two. This, coupled with the fluctuating up-time due to EE implementations on individual units make it difficult to compare their performance.

When the case study plants are benchmarked on a monthly basis, the more advanced Plant C is immediately visible as the most efficient. Plant B, however, shows the most consistent output. As Plant C is exposed to more erratic rain conditions, the increased coal moisture may be responsible for these fluctuations. Plant A shows a higher average efficiency during 2012 when compared to 2013, despite EE interventions in 2013. Plant A also shows evidence of being more efficient under a lower load.

When a three month moving average is applied to plant datasets, certain relationships between plant performance and additional factors come to light. Plant A shows a strong negative correlation to coal moisture. This highlighted relationship may be due to the delay caused by the coal bunker, where coal is analysed and its mass measured before it is sent to the bunker. This means that coal consumption measurements are out of sync with actual consumption values. Using monthly averaging negates this effect to an extent, and is deemed more useful than averaging on a yearly basis.

Classical efficiency methods are thus very well suited to both plant EE tracking and comparative plant EE benchmarking. However, it is difficult to incorporate additional factors, such as climatic, emission and operational variables, and correlations between these datasets and overall plant efficiency are not always easy to identify. Although the comparative benchmarking method allows for a general overview of comparative plant performance, it does not take into account the variations caused by plant design, technology, vintage and operating conditions. Simply stating that Plant B outperforms Plant A because of its higher average efficiency is not an accurate conclusion, as Plant B may do so while having a far higher economic or environmental impact, or environmental conditions may be better suited to its operation.

For future research a higher data sampling rate would lead to a drastic increase in data quality. Quality should also be increased, by using more accurate measuring equipment. This would lead to less data outliers and thus more accurate results. Another potentially useful exercise in determining plant performance would be to evaluate the efficiency of each plant process individually. This would make identifying the source of plant inefficiencies far easier, allowing for the effective application of plant EE efforts

6.2.2.2 Regression analysis conclusions and recommendations

Monthly averaging produced the most accurate results. While the second order polynomial regression consistently produced the best R^2 values, the linear regression is perhaps the best suited when used for M&V baseline adjustment, as it will surely prove more the accurate approximation when datasets are expanded. Higher-fidelity data would also produce more accurate results, as the datasets included in this study were of fairly low quality. A significant R^2 of a regression for plant EE and an additional factor is thus a good indicator of this factor's effect on plant efficiency. For future studies multivariate regression could be examined to provide insight into the combined effects of multiple variables on plant efficiency.

6.2.2.3 Return-to-scale investigation for DEA EE tracking

The RTS orientation which is best suited for DEA EE tracking application was examined. The constant RTS orientation produces the most accurate results when compared to actual normalised efficiency results. However, this is because the actual efficiency calculations are inherently linear in their calculations, thus constant RTS results will always produce more accurate results. This linear nature is desired for pure EE results, making the constant RTS the obvious choice. Even when additional factors are incorporated in the DEA result the focus remains on determining EE.

6.2.2.4 DEA efficiency evaluation conclusions and recommendations

When DEA is applied to an EE comparison between plants results can be used as a quick overview of relative plant performance. However, additional plant information is required to gain insight into the exact sources of inefficiencies. As each plant has unique environmental variables, such as temperature, rainfall etc, these additional datasets should include plant operational and management data e.g. number of employees, hours of planned and unplanned maintenance per month etc.

Fuel mass and calorific content can also be used to comparatively evaluate plants using DEA. This may be difficult, as plants often use different types and qualities of fuel (in the case of this project's case studies, Plant A and Plant B use fuel oil while Plant C uses natural gas, making direct comparisons difficult). These results can, however, provide insight into which plant best utilises its fuel in terms of mass i.e. which plant most effectively processes its fuel. The coal processing equipment, such as pulverisers, of plants deemed inefficient should thus be examined for inefficiencies. When a single plant's EE is evaluated over time using DEA there is limited extra information when compared to a standard EE effort. The same inefficient months are identified. DEA's strength lies in the incorporation of additional factors. Performing a similar analysis using fuel mass and calorific value, it is attempted to highlight which months best process physical quantities of fuel. As fuel calorific data shows very little fluctuation (almost 0% in the case of secondary fuels), these results follow the same trends as EE results and provide no additional information. A higher sampling frequency may be necessary for fuel calorific data and may produce more meaningful results. As coal consumption is measured before the bunker, there exists a "delay" in generation data that must be considered, and may also have an effect on the accuracy of results. This problem is addressed when data averaging is considered.

Rainfall data showed almost no correlation with plant efficiency, despite hypotheses linking rainfall to coal moisture and thus to lowered plant efficiency. The bunker delay may explain this effect. When Plant A's coal moisture content data was incorporated into the DEA certain months were deemed efficient that were not viewed as such before. Thus, months showing exceptional performance despite higher moisture content could be identified. None of the case study plants' DEA efficiency were significantly affected by ambient temperature and thus its effect was not investigated further.

When pollutant datasets (in the case of this project, fuel ash content and fuel sulphur content) are incorporated in a DEA, certain months perform better and/or worse than previously identified. This analysis is referred to as an eco-efficiency evaluation. Results reveal which months performed well while minimising the environmental "cost" associated with higher performance. This could be vital insight when evaluating the environmental impact of a plant. Plant B performs better than the target plant, meaning that less undesirable pollutants are associated with each MWh of electrical energy produced. Plant A management should consider coal scrubbing or similar clean-coal technology so as to bring the plant up to the same environmental standard as achieved by Plant B. Alternatively, more rigorous flue-gas filtration is required to compensate for the additional sulphur and ash associated with Plant A's normal monthly operation.

Using a three month moving average does not provide additional information when used in a DEA EE. Plant A uses low fidelity data, which makes it difficult to identify trends, even when a moving average is employed. However, when coal moisture content data is included, the influence of coal moisture becomes more clear on plant performance. Intelligent metering equipment would be the most accurate way to measure coal consumption, however monthly averaging is a simple solution to the decreasing the data measurement delay between measured and consumed coal. A DEA is performed examining the effect of the three month moving average with fuel mass and calorific data. Certain months are deemed more accurate when mass and calorific data are included, which may indicate months where fuel was effectively processes. Plant B and Plant C's data is of higher quality when compared to Plant A. Plant B's averaged data shows a moderate negative correlation with rainfall data, prompting further investigation. This correlation may also be evidence of time averaging's ability to negate the effects of coal bunker delay on data.

When a yearly average data DEA is performed on the cases study plants, Plant A and Plant B show little to no trending, while Plant C shows results with far less fluctuation. This may be evidence of more accurate data measurement in Plant C (which is far more advanced than either Plant A or Plant B). A moving time average is considered a superior choice to yearly average, as results are more accurate and consistent in these case studies, despite a more limited dataset. Fuel mass and calorific values in DEA efficiency tracking for plants is finally determined to be of little use when used purely for EE evaluation, as no new trends were brought to light in any study. For more useful results fuel mass should ideally be treated as an additional factor in a DEA EE analysis, rather than a separate method of determining efficiency.

In conclusion, when using DEA to comparatively evaluate a number of plants, the sources of inefficiencies may not be easily identified. The efficient plants' practices can be considered for use in inefficient plants as a means of increasing productivity. The process can be used to gain a general insight into the overall efficiency of a single plant in comparison to others an may be useful in the monitoring of large multi-plant projects. By including additional factors, the analysis can be expanded beyond a simple EE ratio exercise.

When used as an efficiency tracking tool for a single plant, DEA also has several strengths and weaknesses. The process can consider additional factors that a simple EE exercise will not consider, giving additional insight into plant performance. The process can also give a general overview of plant performance trends. However, as DEA produces scale efficiency values as results rather than actual efficiency values, it will always be necessary to perform a standard EE study in addition to a DEA. As such, the process cannot serve as a replacement for traditional efficiency monitoring methods, but can be used as a valuable supplementary tool.

Another recommendation for future studies is that DEA may be suited to evaluating the individual sub-systems of a plant as a whole. This requires far more data, but may provide valuable insight as to where inefficiencies occur in the operating cycle of the plant. This method may also be used to compare the performance of multiple plants' subsystems e.g. how efficient the boiler is in a number of separate plants.

This project's scope differs slightly from that of previous studies utilising DEA in power generation, as it focused on a single plant's performance, with emphasis on older plants. While the target plant was benchmarked against other plants, the establishment of its comparative performance remained the ultimate goal. The findings of this project agree to a large extent with those of Yang, Wang, Wen and McGill, who described DEA as less robust in offering referential ways on how to improve power plants' efficiency" and only "provided...modest support for restructuring" [49].

This project served as an exploratory study into the usefulness of DEA-based efficiency tracking in a power plant context, with emphasis on older plants. These older plants usually have very rudimentary metering equipment, bring the accuracy of measured datasets into question. Modern plants often have far more advanced metering equipment, which would produce more accurate data at a higher sampling frequency. As the usefulness of DEA is highly dependent on data quality, the process may produce more usable results when utilised in the efficiency evaluation of more modern plants.

6.3 Further work

For future research in this topic it may be beneficial to evaluate a larger number of plants in a similar context e.g. multiple South African plants or US plants. This may remove some of the ambiguity associated with combining plants of different contexts. Utilisation of the process in a renewable energy plant context may also be a valuable study. Efficiency evaluation methods could perhaps be combined (rather than used individually), providing additional insight into plant performance. Furthermore, higher quality data will lead to more conclusive results. An extremely valuable future study may involve using the methods applied in this study on plant sub-systems (although this is dependent on the availability of plant sub-system data). This would provide insight into inefficiencies in plant operation, rather than evaluating the plant as a single unit.

References

[1] N. M. Odhiambo, “Electricity consumption and economic growth in South Africa: A trivariate causality test,” *Energy Economics,* vol. 31, no. 5, pp. 635-640, 2009.

[2] M. Hoel and S. Kverndokk, “Depletion of fossil fuels and the impact of global warming,” *Resource and Energy Economics,* vol. 18, no. 2, pp. 115-136, 1996.

[3] “Integrated Demand Management,” Eskom Holdings SOC Ltd, 09 02 2015. [Online]. Available: http://www.eskom.co.za/CustomerCare/IDM/Pages/IDM.aspx. [Accessed 09 02 2015].

[4] International Energy Agency; Coal Industry Advisory Board, “Power Generation from Coal: Measuring and Reporting Efficiency Performance and CO2 Emissions,” OECD/IEA, Paris, 2010.

[5] L. Webster and J. Bradford, “M&V Guidelines: Measurement and Verifi cation for Federal Energy Projects Ver 3,” 2008. [Online]. Available: http://www1.eere.energy.gov/femp/pdfs/mv_guidelines.pdf. [Accessed 16 02 2015].

[6] W. de Heijer and L. Grobler, “The Measurement and Verification Guideline for Energy Efficiency and Demand-Side Management(EEDSM) Projects and Programmes,” 2010.

[7] US Energy Information Administration, “eia South Africa,” US Department of Energy, 201. [Online]. Available: http://www.eia.gov/countries/cab.cfm?fips=SF. [Accessed 9 03 2015].

[8] Eskom Holdings SOC Ltd, “Eskom New Build Programme,” 2015. [Online]. Available: www.eskom.co.za/whatweredoing. [Accessed 7 July 2015].

[9] P.-L. Lam and A. Shiu, “A data envelopment analysis of the efficiency of China’s thermal power generation,” *Utilities Policy,* vol. 3, no. 10, p. 75–83, 2001.

[10] H. D. Sherman and J. Zhu, Service Productivity Management: IMproving Service Performance usin Data Envelopment Analysis, Worcester, MA: Springer Science+Business Media, LLC, 2006.

[11] R. J. Campbell, “Increasing the Efficiency of Existing Coal-Fired Power Plants,” Congressional Research Services, Washington DC, 2013.

[12] Y. Zhao, S. Wang, L. Duan, Y. Lei, P. Cao and H. J, “Primary air pollutant emissions of coal-fired

power plants in China: Current status and future prediction," *Atmospheric Environment,* vol. 42, no. 36, pp. 8442-8452, 2008.

[13] G. M. Masters, Renewable and Efficient Electric Power Systems, New Jersey: John Wiley & Sons Inc, 2004.

[14] W. W. Cooper, L. M. Seiford and J. Zhu, Data Envelopment Analysis: History, Models and Interpretations, Worcester, MA: Springer Science+Business Media, LLC, 2011.

[15] S. Yokota and T. Kumano, "Mega-Solar Optimal Allocation Using Data Envelopment Analysis," in *EA4EPQ International Conference on Renewable Energies and Power Quality*, Santiago de Compostela, Spain, 2013.

[16] K. Sarica and I. Or, "Efficiency assessment of Turkish power plants using data envelopment analysis," *Energy,* vol. 32, no. 8, p. 1484–1499, 2007.

[17] P. Korhonen and M. Luptacik, "ECO-EFFICIENCY ANALYSIS OF POWER PLANTS: An extension of DEA," *European journal of operations,* vol. 154, no. 2, p. 437–446, 2004.

[18] G. Iglesias, P. Castellanos and A. Seijas, "Measurement of productive efficiency with frontier methods: A case study for wind farms," *Energy Economics,* vol. 32, no. 5, p. 1199–1208, 2010.

[19] I. Or and K. Sarica, "EFFICIENCY ANALYSIS OF TURKISH POWER PLANTS USING DATA ENVELOPMENT ANALYSIS," in *Asia Pacific Industrial Engineering and Management Systems Conference 2004*, Brisbane, 2004.

[20] K. Mertens, Photovoltaics: Fundamentals, Technology and Practice, London: John Wiley & Sons Ltd, 2014.

[21] B. G. Miller, Coal Energy Systems, Burlington: Elsevier Academic Press, 2005.

[22] M. Burghardt, Engineering Thermodynamics with Applications, New York: Harpercollins College Division , 1986.

[23] A. C. Kadak, *Operational Reactor Safety: Power Cycles for Nuclear Plants: Rankine and Brayton,* Cambridge, Massachusetts: Massachusetts Institute of Technology, 2008.

[24] C. Henderson, "Upgrading and efficiency improvements in coal-fired power plants," IEA Clean

Coal Centre, London, 2013.

[25] R. Kehlhofer, B. Rukes, F. Lannemann and F. Sternimann, Combined-Cycle Gas & Steam Turbine Power Plants, Tulsa: PennWell COrporation, 2009.

[26] F. J. Brooks, “GE Gas Turbine Performance Characteristics,” General Electric Power Systems, New YorkSchenectady, 1997.

[27] P. Zhou, A. BW and P. KL, “A survey of data envelopment analysis in energy and environmental studies,” *European Journal of Operational Research,* vol. 189, no. 1, pp. 1-18, 2008.

[28] B. K. N. Rao, Handbook of Condition Monitoring, Oxford: Elsevier Science Ltd, 1996.

[29] J. Bugge, S. Jaer and R. Blum, “High-efficiency coal-fired power plants development and perspectives,” *Energy,* vol. 31, no. 10-11, p. 1437–1445, 2006.

[30] Columbia University Computer Science dept, “Introduction to Computers, Lecture 26,” 2004. [Online]. Available: http://www.cs.columbia.edu/~gmw/teaching/1001-s04/. [Accessed 10 02 2015].

[31] C. Herrmann and S. Ganscha, “Swiss Federal Istitute of Technology Zurich Computational Biochem Research Group Scientific Databases,” 201. [Online]. Available: http://www.cbrg.ethz.ch/education/SDB. [Accessed 10 02 2015].

[32] E. Codd, “A Relational Model of Data forLarge Shared Data Banks,” *Communications of the ACM,* vol. 13, no. 6, pp. 377-387, 1970.

[33] M. Demba, “ALGORITHM FOR RELATIONAL DATABASE NORMALIZATION UP TO 3NF,” *International Journal of Database Management Systems,* vol. 5, no. 3, pp. 39-51, 2013.

[34] E. F. Codd, The relational model for database management : version 2, Boston: Addison-Wesley, 1990.

[35] N. Schweikardt, T. Schwentick and S. L, Algorithms and theory of computation handbook, London: Chapman & Hall, 2010.

[36] R. J. Dyer, “MySQL in a Nutshell, Second Edition,” O'Reilly Media, Inc, Sebastopol, CA, 2008.

[37] Microsoft, “Microsoft Visual Studio Overview,” Microsoft, 2015. [Online]. Available: http://www.visualstudio.com/products/visual-studio-with-msdn-overview-vs. [Accessed 11 02 2015].

[38] The Eclipse Foundation, “About Eclipse Foundation,” The Eclipse Foundation, 2015. [Online]. Available: https://eclipse.org/org/. [Accessed 11 02 2015].

[39] R. Lischner, Delphi in a Nutshell: A Desktop Quick Reference, Sebastopol: O'Reilly, 2000.

[40] Embarcadero Technologies, “Embarcadero Product Documentation Wikis: Configuring TSQL Connection,” Embarcadero Technologies, 29 6 2014. [Online]. Available: http://docwiki.embarcadero.com/RADStudio/XE6/en/Configuring_TSQL_Connection. [Accessed 12 2 2015].

[41] Microsoft, “Microsoft Developer Network,” Microsoft, 2015. [Online]. Available: https://msdn.microsoft.com/en-us/library/1ez7dh12.aspx. [Accessed 13 02 2015].

[42] SourceForge, “lp_solve reference guide,” SourceForge, 2015. [Online]. Available: http://lpsolve.sourceforge.net/5.5/. [Accessed 16 02 2015].

[43] Free Software Foundation, Inc., “GNU Lesser General Public License, version 2.1,” 02 1999. [Online]. Available: https://www.gnu.org/licenses/lgpl-2.1.html. [Accessed 16 02 2015].

[44] G. Booch, R. Rumbaugh and I. Jacobson, The Unified Modeling Language User Guide, Boston: Addison-Wesley Professional, 1999.

[45] J. Hunt, Guide to the Unified Process featuring UML, Java and Design Patterns, London: Springer, 2003.

[46] D. Montgomery and G. Runger, Applied statistics and probability for engineers, Hoboken: John Wiley and Sons, Inc, 2011.

[47] T. Chai and R. Draxler, “Root mean square error (RMSE) or mean absolute error (MAE)? Arguments against avoiding RMSE in the literature.,” *Geoscientific model development,* vol. 7, no. 3, pp. 1247-1250, 2014.

[48] C. Willmott and K. Matsuura, “Advantages of the mean absolute error (MAE) over the root mean square error (RMSE) in assessing average model performance,” *CLIMATE RESEARCH,* vol.

30, pp. 79-82, 2005.

[49] Explorable.com, "Pearson Product-Moment Correlation," Explorable.com, 8 October 2009. [Online]. Available: https://explorable.com/pearson-product-moment-correlation. [Accessed 8 June 2015].

[50] R. Färe, S. Grosskopf and J. Logan, "The relative efficiency of Illinois electric utilities," *Resources and Energy,* vol. 5, no. 4, pp. 349-367, 1983.

[51] S. Behera, A. Dash and J. Farooquie, "Performance Analysis of Coal fired Power Plants in India," in *International Conference on Industrial Engineering and Operations Management*, Dhaka, 2010.

[52] A. Yang, Q. Wang, F. Wen and I. MacGill, "Data Envelopment Analysis Based Efficiency," in *Sustainable Power Generation and Supply, 2009. SUPERGEN '09. International Conference on*, Nanjing, 2009.

[53] S.-U. Park and J.-B. Lesourde, "The efficiency of conventional fuel power plants in South Korea: A comparison of parametric and non-parametric approaches," *International Journal of Production Economics,* vol. 63, no. 1, p. 59–67, 2000.

[54] T. Chen, T. Yeh and Y. Lee, "Comparison of Power Plants Efficiency among 73 Countries," *Journal of Energy,* vol. 2013, no. 1, pp. 1-8, 2013.

[55] S. Yokota and T. Kumano, "Mega-solar optimal allocation using data envelopment analysis," *Electrical Engineering in Japan,* vol. 183, no. 4, pp. 24-32, 2013.

[56] A. Boussofiane, R. Dyson and T. E, "Applied data envelopment analysis," *European Journal of Operational Research,* vol. 52, no. 1, pp. 1-15, 1991.

[57] S. Kumar and R. Gulati, "An Examination of Technical, Pure Technical, and Scale Efficiencies in Indian Public Sector Banks using Data Envelopment Analysis," *Eurasian Journal of Business and Economics 2008,* vol. 1, no. 2, pp. 33-69, 2008.

[58] L. M. Seiford and R. M. Thrall, "RECENT DEVELOPMENTS IN DEA: The Mathematical Programming Approach to Frontier Analysis," *Journal of Econometrics,* vol. 46, no. 1-2, pp. 7-38, 1990.

[59] R. Dyson, R. Allen, A. Camanho, V. Podinovski, C. Sarrico and E. Shale, “Pitfalls and protocols in DEA,” *European Journal of Operational Research,* vol. 132, no. 2, pp. 245-259, 2001.

[60] J. Farrel, “The Measurement of Productive Efficiency,” *Journal of the Royal Statistics Society,* vol. 120, no. 3, pp. 253-290, 1957.

[61] A. Charnes, W. Cooper and E. Rhodes, “Measuring the efficiency of decision making units,” *European Journal of Operational Research,* vol. 2, pp. 429-444, 1978.

[62] D. G. Luenberger and Y. Ye, Linear and Non Linear Programmin, Stanford: Springer, 2008.

[63] S. Lahaie, “How to take the Dual of a linear Program,” Columbia University, New York, 2008.

Appendix A : Classical energy efficiency results

Appendix A.1 : Plant A daily energy efficiency results

Table A-1: Results of daily energy efficiency analysis for Plant A.

Date	Actual Efficiency	Technical efficiency	Scale efficiency	Heat Rate (MJ/MWh)
2012-01-01	36,83%	111,95%	86,46%	9773,95
2012-01-02	41,09%	124,89%	96,45%	8761,68
2012-01-03	33,39%	101,50%	78,39%	10780,83
2012-01-04	28,82%	87,60%	67,66%	12490,62
2012-01-05	27,57%	83,81%	64,73%	13055,42
2012-01-06	28,89%	87,82%	67,82%	12460,00
2012-01-07	26,17%	79,55%	61,44%	13755,56
2012-01-08	28,53%	86,71%	66,97%	12618,86
2012-01-09	27,13%	82,45%	63,68%	13270,63
2012-01-10	28,20%	85,72%	66,20%	12764,89
2012-01-11	27,45%	83,42%	64,43%	13116,44
2012-01-12	28,79%	87,50%	67,57%	12505,85
2012-01-13	27,21%	82,71%	63,88%	13229,64
2012-01-14	27,29%	82,96%	64,07%	13190,08
2012-01-15	34,55%	105,00%	81,10%	10420,75
2012-01-16	30,11%	91,51%	70,67%	11957,70
2012-01-17	26,10%	79,32%	61,26%	13794,93
2012-01-18	25,58%	77,76%	60,05%	14072,19
2012-01-19	25,95%	78,88%	60,92%	13872,42
2012-01-20	29,12%	88,51%	68,36%	12362,29
2012-01-21	26,76%	81,34%	62,82%	13451,76
2012-01-22	27,01%	82,11%	63,41%	13326,61
2012-01-23	34,53%	104,96%	81,06%	10424,98
2012-01-24	38,17%	116,01%	89,59%	9432,21
2012-01-25	35,09%	106,66%	82,37%	10259,16
2012-01-26	31,73%	96,45%	74,49%	11344,67
2012-01-27	33,02%	100,35%	77,50%	10903,79
2012-01-28	26,52%	80,62%	62,26%	13573,24
2012-01-29	31,92%	97,02%	74,93%	11277,86
2012-01-30	26,01%	79,06%	61,06%	13840,20
2012-01-31	29,60%	89,96%	69,48%	12163,35
2012-02-01	24,76%	75,25%	58,12%	14540,81
2012-02-02	27,33%	83,07%	64,15%	13173,06
2012-02-03	28,57%	86,84%	67,07%	12600,21
2012-02-04	29,66%	90,14%	69,61%	12139,39
2012-02-05	29,55%	89,83%	69,38%	12181,23
2012-02-06	29,18%	88,68%	68,49%	12338,49
2012-02-07	27,10%	82,37%	63,61%	13284,71
2012-02-08	22,46%	68,25%	52,71%	16031,93
2012-02-09	21,19%	64,39%	49,73%	16992,89
2012-02-10	25,32%	76,96%	59,44%	14217,67
2012-02-11	31,71%	96,39%	74,44%	11352,50
2012-02-12	29,04%	88,28%	68,18%	12395,61
2012-02-13	27,89%	84,76%	65,46%	12909,26
2012-02-14	28,10%	85,40%	65,95%	12813,60
2012-02-15	30,79%	93,58%	72,27%	11692,64
2012-02-16	28,17%	85,64%	66,14%	12777,69
2012-02-17	27,75%	84,35%	65,15%	12971,89
2012-02-18	37,04%	112,57%	86,94%	9720,37
2012-02-19	34,90%	106,09%	81,93%	10314,09
2012-02-20	23,69%	72,01%	55,62%	15194,70
2012-02-21	21,77%	66,18%	51,11%	16534,19
2012-02-22	23,85%	72,48%	55,98%	15096,06
2012-02-23	26,43%	80,33%	62,04%	13621,22
2012-02-24	28,11%	85,45%	66,00%	12804,98
2012-02-25	29,90%	90,87%	70,18%	12041,71
2012-02-26	32,18%	97,81%	75,54%	11187,19

Date	Actual Efficiency	Technical efficiency	Scale efficiency	Heat Rate (MJ/MWh)
2012-02-27	35,11%	106,73%	82,43%	10252,36
2012-02-28	30,22%	91,85%	70,94%	11913,12
2012-02-29	27,19%	82,63%	63,82%	13241,94
2012-03-01	25,14%	76,42%	59,02%	14319,36
2012-03-02	23,51%	71,46%	55,19%	15312,27
2012-03-03	25,85%	78,58%	60,69%	13924,80
2012-03-04	35,52%	107,95%	83,37%	10136,08
2012-03-05	29,34%	89,17%	68,87%	12271,49
2012-03-06	26,72%	81,21%	62,72%	13474,08
2012-03-07	27,15%	82,52%	63,73%	13260,63
2012-03-08	24,62%	74,83%	57,79%	14622,47
2012-03-09	27,03%	82,16%	63,46%	13317,63
2012-03-10	26,61%	80,87%	62,45%	13531,13
2012-03-11	24,97%	75,90%	58,62%	14415,85
2012-03-12	24,46%	74,34%	57,41%	14719,58
2012-03-13	26,73%	81,25%	62,75%	13467,56
2012-03-14	26,58%	80,79%	62,40%	13543,26
2012-03-15	34,00%	103,34%	79,81%	10588,25
2012-03-16	30,37%	92,32%	71,30%	11852,76
2012-03-17	42,02%	127,73%	98,65%	8566,45
2012-03-18	34,49%	104,84%	80,97%	10437,06
2012-03-19	27,08%	82,30%	63,56%	13295,17
2012-03-20	24,38%	74,10%	57,23%	14766,24
2012-03-21	26,46%	80,42%	62,11%	13607,17
2012-03-22	24,18%	73,49%	56,76%	14889,56
2012-03-23	26,23%	79,73%	61,58%	13723,43
2012-03-24	30,04%	91,32%	70,53%	11982,58
2012-03-25	28,14%	85,55%	66,07%	12791,11
2012-03-26	26,70%	81,16%	62,68%	13482,36
2012-03-27	23,82%	72,39%	55,91%	15116,03
2012-03-28	27,12%	82,43%	63,66%	13274,02
2012-03-29	25,63%	77,91%	60,17%	14044,83
2012-03-30	26,04%	79,15%	61,13%	13824,33
2012-03-31	35,58%	108,16%	83,53%	10116,86
2012-04-01	33,13%	100,71%	77,78%	10864,74
2012-04-02	29,70%	90,26%	69,71%	12123,01
2012-04-03	30,89%	93,90%	72,52%	11653,46
2012-04-04	31,32%	95,21%	73,53%	11493,24
2012-04-05	30,57%	92,91%	71,75%	11777,84
2012-04-06	30,18%	91,72%	70,84%	11930,20
2012-04-07	28,78%	87,49%	67,57%	12507,44
2012-04-08	32,22%	97,92%	75,62%	11174,89
2012-04-09	31,00%	94,22%	72,77%	11613,02
2012-04-10	31,20%	94,84%	73,25%	11537,00
2012-04-11	31,46%	95,62%	73,84%	11443,98
2012-04-12	30,14%	91,60%	70,74%	11945,67
2012-04-13	29,37%	89,27%	68,95%	12257,15
2012-04-14	30,34%	92,21%	71,22%	11866,04
2012-04-15	30,39%	92,38%	71,34%	11845,32
2012-04-16	32,33%	98,27%	75,90%	11134,33
2012-04-17	31,34%	95,25%	73,56%	11488,08
2012-04-18	34,90%	106,09%	81,93%	10314,40
2012-04-19	31,00%	94,22%	72,77%	11613,25
2012-04-20	30,65%	93,15%	71,94%	11747,21
2012-04-21	30,70%	93,30%	72,06%	11727,57
2012-04-22	33,43%	101,62%	78,48%	10767,70
2012-04-23	32,15%	97,71%	75,47%	11198,24
2012-04-24	34,23%	104,06%	80,36%	10515,60
2012-04-25	30,75%	93,46%	72,18%	11707,95
2012-04-26	30,49%	92,67%	71,57%	11808,12
2012-04-27	31,41%	95,46%	73,72%	11462,95
2012-04-28	30,27%	92,00%	71,05%	11893,98
2012-04-29	29,54%	89,79%	69,34%	12186,57
2012-04-30	30,93%	94,01%	72,61%	11638,95

Date	Actual Efficiency	Technical efficiency	Scale efficiency	Heat Rate (MJ/MWh)
2012-05-01	31,18%	94,76%	73,18%	11547,56
2012-05-02	31,06%	94,42%	72,92%	11589,09
2012-05-03	28,71%	87,28%	67,40%	12537,64
2012-05-04	31,63%	96,14%	74,25%	11381,28
2012-05-05	30,11%	91,53%	70,69%	11954,88
2012-05-06	31,63%	96,14%	74,25%	11381,63
2012-05-07	32,07%	97,48%	75,28%	11225,58
2012-05-08	31,64%	96,16%	74,27%	11378,94
2012-05-09	32,86%	99,87%	77,13%	10957,04
2012-05-10	31,99%	97,25%	75,10%	11252,09
2012-05-11	31,99%	97,25%	75,11%	11251,91
2012-05-12	31,93%	97,05%	74,95%	11274,86
2012-05-13	31,81%	96,69%	74,67%	11317,27
2012-05-14	31,67%	96,25%	74,33%	11368,74
2012-05-15	31,28%	95,09%	73,44%	11507,69
2012-05-16	30,55%	92,87%	71,72%	11782,21
2012-05-17	31,30%	95,13%	73,47%	11502,09
2012-05-18	32,54%	98,91%	76,39%	11062,69
2012-05-19	31,12%	94,59%	73,05%	11568,20
2012-05-20	29,75%	90,43%	69,84%	12100,40
2012-05-21	32,24%	97,98%	75,67%	11167,63
2012-05-22	30,83%	93,71%	72,37%	11676,98
2012-05-23	33,19%	100,89%	77,91%	10846,21
2012-05-24	32,59%	99,05%	76,50%	11046,64
2012-05-25	30,85%	93,78%	72,43%	11667,67
2012-05-26	32,28%	98,11%	75,77%	11153,55
2012-05-27	31,77%	96,58%	74,59%	11330,12
2012-05-28	31,70%	96,35%	74,41%	11356,53
2012-05-29	32,12%	97,63%	75,40%	11207,33
2012-05-30	32,34%	98,30%	75,91%	11131,89
2012-05-31	30,52%	92,76%	71,64%	11796,85
2012-06-01	30,83%	93,71%	72,37%	11676,65
2012-06-02	34,59%	105,15%	81,21%	10406,52
2012-06-03	30,69%	93,29%	72,05%	11728,87
2012-06-04	31,53%	95,85%	74,03%	11416,10
2012-06-05	32,47%	98,68%	76,21%	11088,74
2012-06-06	31,70%	96,36%	74,42%	11355,84
2012-06-07	32,40%	98,48%	76,05%	11111,62
2012-06-08	31,90%	96,95%	74,87%	11286,93
2012-06-09	32,34%	98,31%	75,92%	11130,81
2012-06-10	32,27%	98,09%	75,76%	11154,92
2012-06-11	32,07%	97,48%	75,29%	11224,68
2012-06-12	32,81%	99,72%	77,02%	10972,81
2012-06-13	33,75%	102,60%	79,24%	10665,34
2012-06-14	33,00%	100,30%	77,46%	10909,22
2012-06-15	31,67%	96,25%	74,33%	11368,95
2012-06-16	37,61%	114,32%	88,29%	9571,87
2012-06-17	30,85%	93,76%	72,41%	11670,25
2012-06-18	33,21%	100,93%	77,95%	10840,93
2012-06-19	33,67%	102,34%	79,04%	10692,03
2012-06-20	33,33%	101,31%	78,24%	10801,29
2012-06-21	32,43%	98,59%	76,14%	11099,25
2012-06-22	32,66%	99,27%	76,66%	11023,06
2012-06-23	31,27%	95,04%	73,40%	11512,97
2012-06-24	31,53%	95,84%	74,02%	11416,73
2012-06-25	33,18%	100,85%	77,88%	10850,39
2012-06-26	32,79%	99,65%	76,96%	10980,33
2012-06-27	32,09%	97,52%	75,32%	11219,97
2012-06-28	31,06%	94,41%	72,92%	11589,74
2012-06-29	34,70%	105,46%	81,45%	10375,28
2012-06-30	30,13%	91,59%	70,73%	11947,18
2012-07-01	30,76%	93,51%	72,22%	11701,96
2012-07-02	34,61%	105,21%	81,26%	10400,27
2012-07-03	33,38%	101,45%	78,35%	10786,29

Date	Actual Efficiency	Technical efficiency	Scale efficiency	Heat Rate (MJ/MWh)
2012-07-04	35,49%	107,86%	83,30%	10144,54
2012-07-05	33,80%	102,73%	79,34%	10651,31
2012-07-06	31,47%	95,64%	73,86%	11441,18
2012-07-07	30,10%	91,50%	70,67%	11958,48
2012-07-08	34,59%	105,13%	81,20%	10407,92
2012-07-09	30,65%	93,18%	71,96%	11743,67
2012-07-10	31,83%	96,75%	74,72%	11309,75
2012-07-11	28,43%	86,43%	66,75%	12660,94
2012-07-12	31,95%	97,10%	74,99%	11269,27
2012-07-13	32,48%	98,72%	76,24%	11084,13
2012-07-14	33,71%	102,46%	79,13%	10679,89
2012-07-15	30,85%	93,77%	72,42%	11669,20
2012-07-16	31,45%	95,61%	73,84%	11444,99
2012-07-17	31,38%	95,37%	73,66%	11473,38
2012-07-18	29,58%	89,92%	69,45%	12168,72
2012-07-19	33,71%	102,47%	79,14%	10678,81
2012-07-20	27,57%	83,80%	64,72%	13058,19
2012-07-21	33,97%	103,24%	79,73%	10598,83
2012-07-22	33,78%	102,67%	79,29%	10658,10
2012-07-23	31,58%	95,99%	74,13%	11399,56
2012-07-24	33,74%	102,56%	79,21%	10669,17
2012-07-25	33,47%	101,74%	78,58%	10754,84
2012-07-26	33,64%	102,25%	78,97%	10701,36
2012-07-27	34,54%	104,98%	81,07%	10423,63
2012-07-28	34,84%	105,88%	81,77%	10334,31
2012-07-29	31,86%	96,82%	74,78%	11301,17
2012-07-30	32,50%	98,78%	76,29%	11077,36
2012-07-31	36,76%	111,74%	86,29%	9792,91
2012-08-01	35,03%	106,48%	82,24%	10276,10
2012-08-02	34,68%	105,42%	81,42%	10379,29
2012-08-03	32,89%	99,96%	77,20%	10946,93
2012-08-04	35,76%	108,68%	83,94%	10067,95
2012-08-05	31,60%	96,04%	74,18%	11392,98
2012-08-06	31,03%	94,30%	72,83%	11603,37
2012-08-07	33,77%	102,66%	79,28%	10659,23
2012-08-08	31,34%	95,27%	73,57%	11485,93
2012-08-09	32,33%	98,27%	75,89%	11134,94
2012-08-10	31,84%	96,77%	74,74%	11306,90
2012-08-11	29,65%	90,12%	69,60%	12142,49
2012-08-12	33,85%	102,90%	79,47%	10633,61
2012-08-13	29,50%	89,67%	69,25%	12202,63
2012-08-14	35,52%	107,96%	83,38%	10135,61
2012-08-15	32,03%	97,34%	75,18%	11241,10
2012-08-16	34,03%	103,42%	79,87%	10580,00
2012-08-17	30,93%	94,02%	72,61%	11638,24
2012-08-18	32,08%	97,50%	75,30%	11222,31
2012-08-19	31,47%	95,66%	73,88%	11438,11
2012-08-20	29,64%	90,09%	69,58%	12146,21
2012-08-21	33,88%	102,97%	79,52%	10626,91
2012-08-22	29,68%	90,21%	69,67%	12129,72
2012-08-23	35,30%	107,29%	82,86%	10198,39
2012-08-24	37,28%	113,32%	87,52%	9656,01
2012-08-25	32,30%	98,18%	75,83%	11144,61
2012-08-26	32,78%	99,65%	76,96%	10981,20
2012-08-27	33,19%	100,87%	77,90%	10847,87
2012-08-28	33,70%	102,42%	79,10%	10683,22
2012-08-29	33,08%	100,55%	77,66%	10882,26
2012-08-30	33,27%	101,12%	78,09%	10821,18
2012-08-31	33,84%	102,87%	79,44%	10637,41
2012-09-01	32,93%	100,10%	77,31%	10930,82
2012-09-02	32,72%	99,47%	76,82%	11001,03
2012-09-03	32,55%	98,93%	76,40%	11060,98
2012-09-04	32,68%	99,34%	76,72%	11015,35
2012-09-05	32,64%	99,20%	76,62%	11030,04

Date	Actual Efficiency	Technical efficiency	Scale efficiency	Heat Rate (MJ/MWh)
2012-09-06	32,75%	99,54%	76,88%	10992,67
2012-09-07	33,35%	101,37%	78,29%	10794,64
2012-09-08	32,73%	99,47%	76,82%	11000,28
2012-09-09	23,88%	72,60%	56,07%	15072,76
2012-09-10	31,60%	96,03%	74,17%	11394,04
2012-09-11	32,45%	98,65%	76,19%	11092,41
2012-09-12	31,58%	95,98%	74,13%	11400,53
2012-09-13	33,60%	102,13%	78,88%	10714,12
2012-09-14	32,13%	97,65%	75,42%	11205,20
2012-09-15	33,80%	102,75%	79,35%	10649,78
2012-09-16	32,88%	99,95%	77,19%	10947,98
2012-09-17	31,19%	94,82%	73,23%	11540,46
2012-09-18	32,52%	98,83%	76,33%	11071,36
2012-09-19	32,85%	99,85%	77,12%	10958,52
2012-09-20	33,59%	102,11%	78,86%	10715,95
2012-09-21	33,26%	101,09%	78,07%	10824,10
2012-09-22	33,67%	102,35%	79,04%	10691,39
2012-09-23	33,34%	101,33%	78,26%	10798,62
2012-09-24	31,90%	96,95%	74,88%	11285,95
2012-09-25	32,55%	98,94%	76,41%	11059,11
2012-09-26	32,52%	98,84%	76,34%	11070,36
2012-09-27	32,58%	99,02%	76,47%	11050,74
2012-09-28	32,24%	98,00%	75,69%	11165,13
2012-09-29	31,65%	96,21%	74,31%	11372,94
2012-09-30	33,58%	102,08%	78,83%	10719,58
2012-10-01	31,59%	96,02%	74,16%	11395,59
2012-10-02	31,53%	95,83%	74,01%	11418,38
2012-10-03	32,60%	99,07%	76,52%	11044,57
2012-10-04	30,76%	93,48%	72,20%	11705,14
2012-10-05	33,21%	100,93%	77,95%	10840,89
2012-10-06	32,35%	98,33%	75,94%	11128,12
2012-10-07	31,17%	94,73%	73,16%	11551,40
2012-10-08	33,06%	100,47%	77,60%	10890,70
2012-10-09	34,20%	103,94%	80,27%	10527,84
2012-10-10	33,52%	101,89%	78,69%	10739,72
2012-10-11	33,75%	102,59%	79,23%	10666,42
2012-10-12	31,92%	97,01%	74,92%	11279,67
2012-10-13	31,24%	94,96%	73,34%	11523,48
2012-10-14	31,06%	94,40%	72,90%	11591,55
2012-10-15	30,73%	93,40%	72,13%	11715,81
2012-10-16	32,36%	98,36%	75,96%	11124,94
2012-10-17	32,03%	97,36%	75,19%	11239,05
2012-10-18	33,52%	101,88%	78,69%	10739,82
2012-10-19	32,72%	99,44%	76,80%	11003,97
2012-10-20	32,40%	98,49%	76,06%	11110,07
2012-10-21	33,18%	100,85%	77,88%	10850,44
2012-10-22	33,87%	102,94%	79,50%	10630,18
2012-10-23	32,75%	99,54%	76,88%	10992,28
2012-10-24	32,88%	99,92%	77,17%	10950,50
2012-10-25	32,59%	99,05%	76,50%	11047,06
2012-10-26	33,33%	101,32%	78,25%	10799,84
2012-10-27	32,49%	98,75%	76,27%	11080,59
2012-10-28	31,39%	95,40%	73,68%	11470,03
2012-10-29	35,23%	107,09%	82,71%	10217,73
2012-10-30	31,53%	95,83%	74,01%	11418,41
2012-10-31	32,48%	98,73%	76,25%	11083,40
2012-11-01	32,87%	99,91%	77,16%	10952,04
2012-11-02	30,63%	93,09%	71,90%	11754,12
2012-11-03	31,50%	95,75%	73,95%	11428,41
2012-11-04	33,30%	101,22%	78,17%	10810,26
2012-11-05	32,74%	99,51%	76,85%	10996,06
2012-11-06	31,62%	96,10%	74,22%	11385,94
2012-11-07	31,79%	96,62%	74,62%	11324,92
2012-11-08	33,02%	100,36%	77,51%	10903,46

Date	Actual Efficiency	Technical efficiency	Scale efficiency	Heat Rate (MJ/MWh)
2012-11-09	31,16%	94,70%	73,14%	11554,13
2012-11-10	32,03%	97,36%	75,19%	11238,61
2012-11-11	30,90%	93,92%	72,53%	11650,65
2012-11-12	30,85%	93,78%	72,43%	11668,14
2012-11-13	31,39%	95,40%	73,68%	11469,80
2012-11-14	31,45%	95,58%	73,82%	11448,45
2012-11-15	32,02%	97,31%	75,15%	11244,66
2012-11-16	32,46%	98,65%	76,19%	11092,03
2012-11-17	32,20%	97,86%	75,58%	11181,26
2012-11-18	33,62%	102,19%	78,92%	10707,91
2012-11-19	32,40%	98,49%	76,07%	11109,55
2012-11-20	32,79%	99,66%	76,97%	10979,85
2012-11-21	31,81%	96,69%	74,67%	11316,88
2012-11-22	31,48%	95,68%	73,90%	11435,95
2012-11-23	31,28%	95,08%	73,43%	11508,86
2012-11-24	31,55%	95,90%	74,06%	11410,00
2012-11-25	32,45%	98,63%	76,17%	11094,21
2012-11-26	32,56%	98,97%	76,44%	11055,95
2012-11-27	32,39%	98,46%	76,04%	11113,52
2012-11-28	31,51%	95,77%	73,97%	11425,32
2012-11-29	31,41%	95,46%	73,72%	11462,97
2012-11-30	31,46%	95,64%	73,86%	11441,47
2012-12-01	37,94%	115,33%	89,07%	9487,69
2012-12-02	31,63%	96,13%	74,24%	11383,03
2012-12-03	30,86%	93,79%	72,43%	11667,00
2012-12-04	31,91%	97,00%	74,92%	11280,26
2012-12-05	31,27%	95,06%	73,41%	11511,09
2012-12-06	31,69%	96,32%	74,39%	11360,44
2012-12-07	32,04%	97,40%	75,22%	11234,49
2012-12-08	32,92%	100,07%	77,28%	10934,69
2012-12-09	33,12%	100,68%	77,76%	10868,20
2012-12-10	34,04%	103,46%	79,90%	10576,37
2012-12-11	36,63%	111,34%	85,99%	9828,05
2012-12-12	32,77%	99,61%	76,93%	10984,88
2012-12-13	32,31%	98,21%	75,85%	11141,69
2012-12-14	32,06%	97,45%	75,26%	11228,61
2012-12-15	32,97%	100,23%	77,41%	10917,51
2012-12-16	37,25%	113,24%	87,45%	9663,26
2012-12-17	42,60%	129,48%	100,00%	8450,77
2012-12-18	32,31%	98,22%	75,85%	11140,85
2012-12-19	37,88%	115,12%	88,91%	9504,76
2012-12-20	35,07%	106,59%	82,32%	10265,31
2012-12-21	32,51%	98,81%	76,31%	11074,49
2012-12-22	33,13%	100,70%	77,77%	10865,78
2012-12-23	32,97%	100,22%	77,40%	10918,23
2012-12-24	32,00%	97,27%	75,12%	11249,04
2012-12-25	32,35%	98,33%	75,94%	11128,59
2012-12-26	31,45%	95,58%	73,82%	11448,04
2012-12-27	31,63%	96,13%	74,24%	11382,44
2012-12-28	31,16%	94,71%	73,14%	11554,03
2012-12-29	30,75%	93,46%	72,18%	11707,92
2012-12-30	31,59%	96,03%	74,16%	11394,71
2012-12-31	30,75%	93,47%	72,19%	11706,64
2013-01-01	33,02%	100,36%	77,51%	10902,64
2013-01-02	32,50%	98,79%	76,30%	11076,05
2013-01-03	33,74%	102,56%	79,21%	10668,76
2013-01-04	33,34%	101,33%	78,26%	10798,10
2013-01-05	32,96%	100,18%	77,37%	10922,87
2013-01-06	30,52%	92,76%	71,64%	11796,53
2013-01-07	32,29%	98,14%	75,80%	11149,28
2013-01-08	32,65%	99,24%	76,64%	11026,04
2013-01-09	30,18%	91,72%	70,83%	11930,37
2013-01-10	32,57%	98,99%	76,45%	11054,15
2013-01-11	32,18%	97,80%	75,53%	11188,31

Date	Actual Efficiency	Technical efficiency	Scale efficiency	Heat Rate (MJ/MWh)
2013-01-12	33,69%	102,41%	79,09%	10685,13
2013-01-13	33,10%	100,62%	77,71%	10874,69
2013-01-14	31,49%	95,72%	73,93%	11431,01
2013-01-15	32,41%	98,53%	76,09%	11106,02
2013-01-16	33,18%	100,86%	77,89%	10849,42
2013-01-17	32,34%	98,30%	75,92%	11131,60
2013-01-18	31,86%	96,83%	74,79%	11300,02
2013-01-19	32,51%	98,82%	76,32%	11072,53
2013-01-20	32,14%	97,68%	75,44%	11202,36
2013-01-21	31,33%	95,21%	73,53%	11492,37
2013-01-22	31,35%	95,30%	73,60%	11481,75
2013-01-23	31,89%	96,93%	74,86%	11289,23
2013-01-24	31,44%	95,55%	73,79%	11451,73
2013-01-25	31,92%	97,03%	74,94%	11276,95
2013-01-26	30,73%	93,40%	72,13%	11715,24
2013-01-27	31,03%	94,32%	72,84%	11601,38
2013-01-28	31,60%	96,04%	74,17%	11394,02
2013-01-29	32,05%	97,43%	75,25%	11230,89
2013-01-30	32,21%	97,89%	75,60%	11177,97
2013-01-31	31,88%	96,89%	74,83%	11293,65
2013-02-01	31,08%	94,48%	72,97%	11581,51
2013-02-02	31,94%	97,08%	74,98%	11271,01
2013-02-03	31,38%	95,38%	73,66%	11472,19
2013-02-04	31,37%	95,36%	73,64%	11475,13
2013-02-05	30,74%	93,44%	72,16%	11710,37
2013-02-06	30,74%	93,43%	72,16%	11711,33
2013-02-07	29,94%	91,01%	70,29%	12023,57
2013-02-08	28,96%	88,03%	67,99%	12429,44
2013-02-09	29,80%	90,58%	69,96%	12080,24
2013-02-10	29,33%	89,15%	68,85%	12273,86
2013-02-11	28,65%	87,08%	67,25%	12565,64
2013-02-12	30,76%	93,49%	72,20%	11704,69
2013-02-13	37,16%	112,94%	87,23%	9688,20
2013-02-14	29,88%	90,82%	70,14%	12048,83
2013-02-15	28,80%	87,53%	67,60%	12501,58
2013-02-16	30,79%	93,59%	72,28%	11691,36
2013-02-17	35,32%	107,35%	82,90%	10193,35
2013-02-18	31,20%	94,82%	73,23%	11539,49
2013-02-19	34,42%	104,61%	80,79%	10460,50
2013-02-20	30,53%	92,80%	71,67%	11790,72
2013-02-21	28,89%	87,82%	67,83%	12459,49
2013-02-22	29,13%	88,53%	68,37%	12360,09
2013-02-23	29,75%	90,44%	69,85%	12099,32
2013-02-24	29,89%	90,84%	70,16%	12045,65
2013-02-25	33,46%	101,72%	78,56%	10757,55
2013-02-26	29,76%	90,47%	69,87%	12094,94
2013-02-27	30,40%	92,40%	71,36%	11842,78
2013-02-28	32,34%	98,30%	75,92%	11131,12
2013-03-01	30,64%	93,13%	71,92%	11749,66
2013-03-02	31,09%	94,49%	72,97%	11580,90
2013-03-03	30,42%	92,46%	71,41%	11833,97
2013-03-04	31,30%	95,14%	73,48%	11500,84
2013-03-05	31,51%	95,78%	73,97%	11424,72
2013-03-06	31,71%	96,38%	74,43%	11353,27
2013-03-07	30,61%	93,03%	71,84%	11762,66
2013-03-08	30,85%	93,76%	72,41%	11670,63
2013-03-09	31,88%	96,91%	74,84%	11291,15
2013-03-10	30,52%	92,77%	71,65%	11794,52
2013-03-11	31,45%	95,60%	73,84%	11445,27
2013-03-12	30,48%	92,64%	71,55%	11811,82
2013-03-13	31,88%	96,89%	74,83%	11293,48
2013-03-14	31,89%	96,92%	74,85%	11290,49
2013-03-15	30,61%	93,04%	71,86%	11760,69
2013-03-16	29,76%	90,44%	69,85%	12098,62

Date	Actual Efficiency	Technical efficiency	Scale efficiency	Heat Rate (MJ/MWh)
2013-03-17	26,59%	80,83%	62,42%	13537,57
2013-03-18	28,17%	85,63%	66,13%	12778,87
2013-03-19	32,82%	99,76%	77,04%	10968,82
2013-03-20	30,17%	91,70%	70,82%	11932,79
2013-03-21	30,32%	92,14%	71,16%	11875,23
2013-03-22	30,09%	91,47%	70,64%	11962,78
2013-03-23	33,19%	100,87%	77,91%	10847,42
2013-03-24	32,62%	99,14%	76,57%	11037,34
2013-03-25	32,41%	98,52%	76,09%	11106,68
2013-03-26	28,64%	87,07%	67,24%	12567,87
2013-03-27	27,75%	84,34%	65,13%	12974,29
2013-03-28	31,89%	96,92%	74,85%	11289,56
2013-03-29	29,78%	90,52%	69,91%	12088,61
2013-03-30	29,79%	90,56%	69,94%	12082,88
2013-03-31	33,59%	102,10%	78,86%	10716,78
2013-04-01	31,96%	97,16%	75,03%	11262,64
2013-04-02	32,18%	97,82%	75,55%	11186,19
2013-04-03	30,90%	93,92%	72,53%	11651,11
2013-04-04	29,18%	88,70%	68,50%	12336,22
2013-04-05	29,75%	90,42%	69,84%	12100,92
2013-04-06	28,90%	87,83%	67,83%	12458,41
2013-04-07	35,58%	108,16%	83,53%	10116,84
2013-04-08	28,92%	87,89%	67,88%	12449,96
2013-04-09	29,11%	88,47%	68,33%	12367,65
2013-04-10	30,10%	91,50%	70,67%	11958,78
2013-04-11	29,19%	88,74%	68,53%	12331,07
2013-04-12	29,85%	90,74%	70,08%	12059,54
2013-04-13	29,55%	89,81%	69,36%	12183,51
2013-04-14	31,78%	96,59%	74,60%	11328,25
2013-04-15	28,43%	86,42%	66,74%	12662,15
2013-04-16	30,70%	93,33%	72,08%	11724,52
2013-04-17	28,57%	86,83%	67,06%	12601,55
2013-04-18	30,83%	93,72%	72,38%	11676,08
2013-04-19	26,26%	79,82%	61,65%	13708,71
2013-04-20	31,42%	95,49%	73,75%	11459,24
2013-04-21	31,17%	94,74%	73,17%	11549,28
2013-04-22	30,83%	93,70%	72,37%	11677,61
2013-04-23	30,23%	91,88%	70,96%	11908,97
2013-04-24	26,88%	81,70%	63,10%	13393,70
2013-04-25	32,66%	99,27%	76,67%	11022,22
2013-04-26	31,69%	96,31%	74,38%	11361,03
2013-04-27	32,99%	100,26%	77,44%	10913,34
2013-04-28	33,01%	100,35%	77,50%	10904,14
2013-04-29	30,62%	93,06%	71,87%	11758,86
2013-04-30	32,21%	97,92%	75,62%	11175,08
2013-05-01	30,86%	93,81%	72,45%	11664,38
2013-05-02	30,28%	92,03%	71,08%	11889,58
2013-05-03	28,26%	85,90%	66,34%	12738,60
2013-05-04	28,81%	87,56%	67,63%	12496,33
2013-05-05	28,31%	86,04%	66,45%	12717,66
2013-05-06	28,53%	86,72%	66,98%	12617,65
2013-05-07	29,53%	89,76%	69,32%	12190,20
2013-05-08	31,38%	95,39%	73,67%	11471,47
2013-05-09	30,42%	92,48%	71,42%	11832,55
2013-05-10	29,06%	88,32%	68,21%	12390,01
2013-05-11	27,02%	82,13%	63,43%	13322,50
2013-05-12	28,64%	87,04%	67,22%	12571,25
2013-05-13	33,97%	103,26%	79,75%	10596,63
2013-05-14	31,32%	95,19%	73,52%	11495,27
2013-05-15	32,16%	97,76%	75,50%	11193,48
2013-05-16	31,79%	96,64%	74,63%	11322,92
2013-05-17	28,21%	85,76%	66,23%	12759,23
2013-05-18	27,80%	84,50%	65,26%	12948,89
2013-05-19	27,46%	83,45%	64,45%	13111,84

Date	Actual Efficiency	Technical efficiency	Scale efficiency	Heat Rate (MJ/MWh)
2013-05-20	28,73%	87,34%	67,45%	12528,69
2013-05-21	30,66%	93,20%	71,98%	11740,09
2013-05-22	28,64%	87,05%	67,23%	12570,11
2013-05-23	29,58%	89,92%	69,45%	12168,57
2013-05-24	29,34%	89,18%	68,87%	12270,53
2013-05-25	29,52%	89,72%	69,29%	12195,95
2013-05-26	29,56%	89,84%	69,39%	12179,37
2013-05-27	28,38%	86,26%	66,62%	12685,53
2013-05-28	29,49%	89,63%	69,22%	12207,98
2013-05-29	28,91%	87,86%	67,85%	12454,31
2013-05-30	27,92%	84,87%	65,54%	12893,43
2013-05-31	26,49%	80,51%	62,18%	13590,45
2013-06-01	26,73%	81,25%	62,75%	13466,76
2013-06-02	28,75%	87,39%	67,50%	12520,49
2013-06-03	27,27%	82,88%	64,01%	13202,88
2013-06-04	27,75%	84,35%	65,14%	12972,80
2013-06-05	28,28%	85,96%	66,38%	12730,00
2013-06-06	28,69%	87,20%	67,34%	12548,66
2013-06-07	29,00%	88,14%	68,07%	12414,98
2013-06-08	28,43%	86,41%	66,74%	12662,73
2013-06-09	26,59%	80,82%	62,42%	13538,56
2013-06-10	29,62%	90,02%	69,52%	12155,33
2013-06-11	29,37%	89,26%	68,94%	12258,25
2013-06-12	28,92%	87,90%	67,88%	12448,95
2013-06-13	27,27%	82,90%	64,02%	13199,37
2013-06-14	26,99%	82,03%	63,35%	13339,77
2013-06-15	27,37%	83,20%	64,26%	13151,75
2013-06-16	27,37%	83,19%	64,25%	13152,70
2013-06-17	30,23%	91,88%	70,96%	11909,52
2013-06-18	27,02%	82,13%	63,43%	13322,60
2013-06-19	28,52%	86,69%	66,95%	12622,15
2013-06-20	29,55%	89,83%	69,38%	12181,21
2013-06-21	28,84%	87,66%	67,70%	12482,36
2013-06-22	29,19%	88,71%	68,51%	12334,41
2013-06-23	27,70%	84,20%	65,03%	12994,87
2013-06-24	29,28%	88,99%	68,73%	12296,42
2013-06-25	32,02%	97,33%	75,17%	11242,63
2013-06-26	31,61%	96,08%	74,21%	11388,33
2013-06-27	28,59%	86,90%	67,11%	12591,94
2013-06-28	31,85%	96,80%	74,76%	11304,47
2013-06-29	30,66%	93,20%	71,98%	11740,84
2013-06-30	31,71%	96,39%	74,44%	11352,04
2013-07-01	33,80%	102,72%	79,34%	10652,00
2013-07-02	28,28%	85,97%	66,40%	12727,70
2013-07-03	27,95%	84,95%	65,61%	12880,93
2013-07-04	29,90%	90,87%	70,18%	12041,70
2013-07-05	29,54%	89,79%	69,35%	12186,45
2013-07-06	29,88%	90,82%	70,14%	12048,91
2013-07-07	30,31%	92,12%	71,15%	11877,96
2013-07-08	29,81%	90,61%	69,98%	12076,06
2013-07-09	30,26%	91,98%	71,04%	11896,10
2013-07-10	30,11%	91,51%	70,67%	11957,66
2013-07-11	29,77%	90,48%	69,88%	12093,18
2013-07-12	26,25%	79,80%	61,63%	13711,92
2013-07-13	27,46%	83,46%	64,46%	13110,50
2013-07-14	28,44%	86,45%	66,77%	12657,46
2013-07-15	28,23%	85,80%	66,26%	12753,72
2013-07-16	31,32%	95,21%	73,53%	11492,45
2013-07-17	29,87%	90,80%	70,12%	12051,30
2013-07-18	27,38%	83,22%	64,27%	13147,92
2013-07-19	29,05%	88,28%	68,18%	12394,37
2013-07-20	27,95%	84,95%	65,60%	12881,40
2013-07-21	29,94%	91,00%	70,28%	12024,63
2013-07-22	29,39%	89,33%	68,99%	12249,30

Date	Actual Efficiency	Technical efficiency	Scale efficiency	Heat Rate (MJ/MWh)
2013-07-23	30,14%	91,60%	70,74%	11945,80
2013-07-24	30,04%	91,30%	70,51%	11985,12
2013-07-25	30,46%	92,58%	71,50%	11818,67
2013-07-26	30,34%	92,23%	71,23%	11864,22
2013-07-27	32,23%	97,95%	75,65%	11170,85
2013-07-28	32,60%	99,10%	76,53%	11041,74
2013-07-29	31,39%	95,41%	73,69%	11468,71
2013-07-30	30,09%	91,46%	70,64%	11963,95
2013-07-31	31,48%	95,67%	73,89%	11437,26
2013-08-01	30,26%	91,98%	71,03%	11896,97
2013-08-02	31,38%	95,38%	73,66%	11472,36
2013-08-03	26,61%	80,89%	62,47%	13526,73
2013-08-04	29,07%	88,35%	68,23%	12385,43
2013-08-05	29,79%	90,55%	69,93%	12084,56
2013-08-06	30,93%	94,02%	72,61%	11638,12
2013-08-07	30,82%	93,69%	72,36%	11679,33
2013-08-08	28,82%	87,60%	67,65%	12491,20
2013-08-09	28,75%	87,39%	67,49%	12521,81
2013-08-10	25,76%	78,31%	60,48%	13973,22
2013-08-11	26,06%	79,20%	61,16%	13816,57
2013-08-12	27,01%	82,11%	63,41%	13326,27
2013-08-13	27,38%	83,22%	64,27%	13148,66
2013-08-14	28,39%	86,28%	66,64%	12681,67
2013-08-15	27,88%	84,75%	65,45%	12911,78
2013-08-16	29,66%	90,14%	69,61%	12139,49
2013-08-17	29,40%	89,36%	69,01%	12244,85
2013-08-18	31,36%	95,31%	73,61%	11481,14
2013-08-19	27,32%	83,05%	64,14%	13175,78
2013-08-20	27,72%	84,26%	65,07%	12986,94
2013-08-21	26,25%	79,78%	61,62%	13714,75
2013-08-22	27,43%	83,38%	64,40%	13122,80
2013-08-23	28,84%	87,66%	67,70%	12481,97
2013-08-24	29,66%	90,16%	69,63%	12136,01
2013-08-25	27,59%	83,86%	64,77%	13047,47
2013-08-26	30,40%	92,39%	71,36%	11842,93
2013-08-27	26,85%	81,61%	63,03%	13407,76
2013-08-28	27,15%	82,53%	63,74%	13258,64
2013-08-29	27,63%	83,98%	64,86%	13029,80
2013-08-30	33,43%	101,61%	78,47%	10768,88
2013-08-31	28,43%	86,40%	66,73%	12664,78
2013-09-01	27,83%	84,60%	65,34%	12934,40
2013-09-02	29,51%	89,71%	69,28%	12197,78
2013-09-03	27,51%	83,61%	64,57%	13087,32
2013-09-04	26,20%	79,64%	61,50%	13740,03
2013-09-05	23,14%	70,32%	54,31%	15559,82
2013-09-06	21,50%	65,35%	50,47%	16743,55
2013-09-07	32,83%	99,78%	77,06%	10966,03
2013-09-08	21,85%	66,42%	51,30%	16473,61
2013-09-09	25,72%	78,16%	60,37%	13999,33
2013-09-10	27,44%	83,39%	64,41%	13121,18
2013-09-11	40,08%	121,82%	94,09%	8982,06
2013-09-12	23,47%	71,33%	55,09%	15339,39
2013-09-13	27,98%	85,06%	65,69%	12864,41
2013-09-14	30,67%	93,21%	71,99%	11739,30
2013-09-15	27,38%	83,22%	64,27%	13148,48
2013-09-16	24,95%	75,84%	58,57%	14427,99
2013-09-17	28,13%	85,49%	66,03%	12798,79
2013-09-18	25,18%	76,54%	59,11%	14296,72
2013-09-19	24,88%	75,63%	58,41%	14468,93
2013-09-20	39,40%	119,75%	92,49%	9137,20
2013-09-21	29,56%	89,85%	69,39%	12178,04
2013-09-22	29,88%	90,82%	70,14%	12047,86
2013-09-23	26,25%	79,80%	61,63%	13712,41
2013-09-24	22,23%	67,56%	52,17%	16197,13

Date	Actual Efficiency	Technical efficiency	Scale efficiency	Heat Rate (MJ/MWh)
2013-09-25	27,70%	84,19%	65,02%	12996,88
2013-09-26	27,56%	83,77%	64,69%	13062,95
2013-09-27	27,85%	84,66%	65,38%	12925,47
2013-09-28	27,07%	82,27%	63,54%	13300,53
2013-09-29	27,72%	84,26%	65,08%	12986,13
2013-09-30	36,81%	111,88%	86,41%	9780,32
2013-10-01	34,46%	104,75%	80,90%	10446,15
2013-10-02	30,44%	92,51%	71,45%	11828,06
2013-10-03	29,35%	89,21%	68,90%	12265,45
2013-10-04	27,67%	84,12%	64,96%	13008,19
2013-10-05	30,16%	91,66%	70,79%	11937,27
2013-10-06	30,79%	93,57%	72,27%	11693,64
2013-10-07	36,28%	110,26%	85,16%	9923,65
2013-10-08	27,57%	83,81%	64,73%	13055,47
2013-10-09	28,96%	88,04%	67,99%	12429,13
2013-10-10	31,18%	94,77%	73,19%	11545,78
2013-10-11	30,68%	93,27%	72,03%	11732,17
2013-10-12	27,59%	83,86%	64,77%	13048,19
2013-10-13	32,30%	98,17%	75,82%	11146,18
2013-10-14	31,74%	96,46%	74,50%	11343,48
2013-10-15	30,50%	92,71%	71,60%	11802,40
2013-10-16	27,36%	83,16%	64,23%	13157,87
2013-10-17	25,93%	78,82%	60,87%	13882,80
2013-10-18	30,23%	91,87%	70,95%	11910,56
2013-10-19	23,91%	72,67%	56,13%	15056,97
2013-10-20	28,49%	86,60%	66,88%	12635,21
2013-10-21	26,81%	81,50%	62,94%	13426,28
2013-10-22	34,78%	105,72%	81,65%	10350,13
2013-10-23	31,32%	95,19%	73,51%	11495,37
2013-10-24	37,22%	113,14%	87,38%	9671,24
2013-10-25	33,59%	102,10%	78,86%	10716,80
2013-10-26	31,19%	94,79%	73,21%	11543,36
2013-10-27	31,13%	94,63%	73,08%	11563,48
2013-10-28	45,13%	137,16%	105,93%	7977,67
2013-10-29	27,71%	84,21%	65,04%	12993,52
2013-10-30	31,98%	97,21%	75,08%	11256,42
2013-10-31	30,18%	91,75%	70,86%	11926,55
2013-11-01	32,48%	98,71%	76,24%	11084,81
2013-11-02	30,68%	93,25%	72,02%	11733,81
2013-11-03	26,22%	79,70%	61,55%	13729,61
2013-11-04	29,48%	89,62%	69,21%	12209,61
2013-11-05	38,87%	118,16%	91,26%	9260,59
2013-11-06	24,86%	75,56%	58,36%	14480,64
2013-11-07	29,72%	90,32%	69,76%	12114,38
2013-11-08	32,17%	97,79%	75,53%	11189,33
2013-11-09	29,24%	88,88%	68,65%	12310,60
2013-11-10	33,89%	103,00%	79,55%	10623,83
2013-11-11	28,88%	87,79%	67,80%	12464,77
2013-11-12	34,21%	104,00%	80,32%	10521,76
2013-11-13	27,76%	84,38%	65,17%	12967,73
2013-11-14	34,72%	105,54%	81,51%	10367,68
2013-11-15	31,80%	96,66%	74,65%	11320,54
2013-11-16	34,68%	105,42%	81,42%	10379,55
2013-11-17	33,43%	101,60%	78,47%	10769,47
2013-11-18	31,02%	94,29%	72,82%	11605,00
2013-11-19	31,89%	96,93%	74,86%	11288,38
2013-11-20	32,62%	99,16%	76,58%	11034,75
2013-11-21	31,45%	95,58%	73,82%	11447,82
2013-11-22	26,81%	81,49%	62,93%	13427,86
2013-11-23	33,24%	101,02%	78,02%	10831,74
2013-11-24	33,46%	101,71%	78,55%	10757,81
2013-11-25	31,33%	95,24%	73,55%	11489,39
2013-11-26	27,02%	82,11%	63,42%	13325,80
2013-11-27	35,26%	107,19%	82,78%	10208,46

Date	Actual Efficiency	Technical efficiency	Scale efficiency	Heat Rate (MJ/MWh)
2013-11-28	28,96%	88,02%	67,98%	12432,04
2013-11-29	29,91%	90,91%	70,21%	12036,84
2013-11-30	31,85%	96,81%	74,77%	11302,87
2013-12-01	31,05%	94,37%	72,88%	11595,02
2013-12-02	24,24%	73,68%	56,90%	14851,18
2013-12-03	32,76%	99,58%	76,90%	10988,89
2013-12-04	32,25%	98,04%	75,71%	11161,42
2013-12-05	34,91%	106,11%	81,95%	10312,21
2013-12-06	28,36%	86,21%	66,58%	12692,15
2013-12-07	30,79%	93,57%	72,27%	11693,88
2013-12-08	37,28%	113,31%	87,51%	9657,29
2013-12-09	36,24%	110,16%	85,08%	9932,61
2013-12-10	30,13%	91,59%	70,74%	11946,59
2013-12-11	35,95%	109,28%	84,40%	10013,10
2013-12-12	32,86%	99,87%	77,13%	10956,29
2013-12-13	27,95%	84,95%	65,61%	12880,95
2013-12-14	29,19%	88,72%	68,52%	12333,22
2013-12-15	36,03%	109,53%	84,59%	9990,36
2013-12-16	26,09%	79,31%	61,25%	13797,03
2013-12-17	26,42%	80,31%	62,02%	13625,61
2013-12-18	23,71%	72,05%	55,65%	15186,34
2013-12-19	31,38%	95,38%	73,66%	11471,91
2013-12-20	37,36%	113,55%	87,70%	9636,21
2013-12-21	29,50%	89,66%	69,24%	12204,24
2013-12-22	31,90%	96,97%	74,89%	11284,56
2013-12-23	27,80%	84,50%	65,26%	12949,56
2013-12-24	32,42%	98,54%	76,11%	11103,92
2013-12-25	28,82%	87,60%	67,66%	12490,84
2013-12-26	25,26%	76,78%	59,29%	14252,17
2013-12-27	32,90%	100,00%	77,23%	10942,00
2013-12-28	33,61%	102,16%	78,90%	10710,67
2013-12-29	25,75%	78,26%	60,44%	13981,26
2013-12-30	33,40%	101,53%	78,41%	10777,25
2013-12-31	22,74%	69,11%	53,38%	15832,74

Appendix A.2 : Monthly energy efficiency results

Table A-2: *Monthly energy efficiencies of case study plants.*

	Plant A efficiency	Plant B efficiency	Plant C efficiency
Jan-12	29,50%	32,54%	32,85%
Feb-12	27,74%	28,76%	33,17%
Mar-12	27,44%	31,59%	36,88%
Apr-12	29,35%	31,75%	35,56%
May-12	29,98%	31,61%	33,31%
Jun-12	30,51%	31,66%	33,19%
Jul-12	30,66%	31,69%	36,78%
Aug-12	31,45%	31,80%	31,57%
Sep-12	31,03%	31,86%	31,63%
Oct-12	31,21%	32,10%	32,80%
Nov-12	31,06%	32,12%	33,83%
Dec-12	31,37%	31,94%	34,64%
Jan-13	29,92%	31,85%	32,97%
Feb-13	29,19%	31,44%	32,76%
Mar-13	29,21%	31,86%	30,61%
Apr-13	29,36%	31,48%	33,59%

May-13	27,34%	31,07%	32,86%
Jun-13	27,23%	30,62%	33,73%
Jul-13	27,76%	30,98%	32,84%
Aug-13	27,12%	31,01%	33,23%
Sep-13	25,89%	30,97%	32,32%
Oct-13	28,93%	31,00%	33,77%
Nov-13	29,93%	30,04%	34,09%
Dec-13	28,63%	29,92%	32,59%

***Table A-3**: Monthly unit up-time for Plant A.*

	unit 1	unit 2	unit 3	unit 4	unit 5	unit 6
Jan-12	100,00%	0,00%	90,32%	93,55%	96,77%	100,00%
Feb-12	100,00%	0,00%	100,00%	75,86%	93,10%	86,21%
Mar-12	100,00%	0,00%	87,10%	67,74%	100,00%	54,84%
Apr-12	100,00%	0,00%	100,00%	33,33%	90,00%	96,67%
May-12	93,55%	54,84%	87,10%	100,00%	100,00%	100,00%
Jun-12	3,33%	100,00%	100,00%	96,67%	100,00%	100,00%
Jul-12	0,00%	96,88%	96,88%	96,88%	68,75%	96,88%
Aug-12	0,00%	100,00%	93,55%	100,00%	100,00%	100,00%
Sep-12	0,00%	100,00%	96,77%	93,55%	90,32%	96,77%
Oct-12	0,00%	100,00%	20,00%	100,00%	100,00%	96,67%
Nov-12	0,00%	83,33%	100,00%	90,00%	66,67%	10,00%
Dec-12	0,00%	100,00%	64,52%	87,10%	0,00%	12,90%

Appendix B : DEA energy efficiency results

Appendix B.1 : Return-to-scale DEA results

***Table B-1**: Various RTS EE results for Plant A.*

	Actual normalised	Constant RTS	Variable RTS	Non-increasing RTS	Non-decreasing RTS
Jan-12	0,9380	0,9430	0,9508	0,9508	0,9430
Feb-12	0,8820	0,8864	0,8920	0,8920	0,8864
Mar-12	0,8725	0,8813	0,8844	0,8844	0,8813
Apr-12	0,9330	0,9366	0,9394	0,9394	0,9366
May-12	0,9533	0,9603	0,9642	0,9642	0,9603
Jun-12	0,9701	0,9733	0,9757	0,9757	0,9733
Jul-12	0,9748	0,9775	0,9785	0,9785	0,9775
Aug-12	1,0000	1,0000	1,0000	1,0000	1,0000
Sep-12	0,9866	0,9921	1,0000	1,0000	0,9921
Oct-12	0,9923	1,0000	1,0000	1,0000	1,0000
Nov-12	0,9875	1,0000	1,0000	1,0000	1,0000
Dec-12	0,9972	1,0000	1,0000	1,0000	1,0000
Jan-13	0,9540	0,9590	0,5807	0,9590	0,9507
Feb-13	0,9221	0,9252	1,0000	0,9252	1,0000
Mar-13	0,9270	0,9346	0,9660	0,9660	0,9346
Apr-13	0,9128	0,8725	0,9373	0,9373	0,9244
May-13	0,8669	0,8710	0,8828	0,8828	0,8710
Jun-13	0,8539	0,8565	0,9541	0,9566	0,8565
Jul-13	0,8836	0,8866	1,0000	1,0000	0,8866
Aug-13	0,8514	0,8537	0,9440	0,9440	0,8537
Sep-13	0,8091	0,8138	0,8495	0,8495	0,8138
Oct-13	0,8902	0,8664	0,8664	0,8664	0,8664
Nov-13	0,9300	0,9431	1,0000	1,0000	0,9431
Dec-13	0,8856	0,8591	0,9097	0,9097	0,8349

***Table B-2**: Various RTS EE results for Plant B.*

	Actual normalised	Constant RTS	Variable RTS	Non-increasing RTS	Non-decreasing RTS
Jan-12	1,0000	1,0000	1,0000	1,0000	1,0000

	Actual normalised	Constant RTS	Variable RTS	Non-increasing RTS	Non-decreasing RTS
Feb-12	0,8841	0,8914	0,8943	0,8914	0,8943
Mar-12	0,9711	0,9746	0,9793	0,9746	0,9793
Apr-12	0,9759	0,9836	1,0000	0,9836	1,0000
May-12	0,9714	0,9718	0,9824	0,9718	0,9824
Jun-12	0,9730	0,9781	0,9844	0,9781	0,9844
Jul-12	0,9739	0,9801	0,9803	0,9801	0,9803
Aug-12	0,9772	0,9890	1,0000	1,0000	0,9890
Sep-12	0,9791	0,9808	1,0000	0,9808	1,0000
Oct-12	0,9867	0,9884	0,9964	0,9884	0,9964
Nov-12	0,9873	0,9941	0,9945	0,9941	0,9945
Dec-12	0,9816	1,0000	1,0000	1,0000	1,0000
Jan-13	0,9791	0,9799	0,9841	0,9799	0,9841
Feb-13	0,9662	0,9665	0,9809	0,9665	0,9809
Mar-13	0,9792	0,9798	0,9910	0,9798	0,9910
Apr-13	0,9674	0,9722	0,9854	0,9722	0,9854
May-13	0,9548	0,9561	0,9663	0,9561	0,9663
Jun-13	0,9412	0,9426	0,9499	0,9426	0,9499
Jul-13	0,9522	0,9536	0,9595	0,9536	0,9595
Aug-13	0,9531	0,9636	0,9689	0,9636	0,9689
Sep-13	0,9519	0,9537	0,9634	0,9537	0,9634
Oct-13	0,9528	0,9545	1,0000	0,9545	1,0000
Nov-13	0,9233	0,9241	0,9327	0,9241	0,9327
Dec-13	0,9197	0,9269	0,9323	0,9269	0,9323

***Table B-3**: Various RTS EE results for Plant C.*

	Actual normalised	Constant RTS	Variable RTS	Non-increasing RTS	Non-decreasing RTS
Jan-12	0,8907	0,8914	0,9598	0,8914	0,9598
Feb-12	0,8994	0,9044	0,9288	0,9044	0,9288
Mar-12	1,0000	1,0000	1,0000	1,0000	1,0000
Apr-12	0,9642	0,9808	1,0000	0,9808	1,0000
May-12	0,9034	0,9103	1,0000	0,9103	1,0000
Jun-12	0,9001	0,9583	0,9588	0,9588	0,9583
Jul-12	0,9973	1,0000	1,0000	1,0000	1,0000
Aug-12	0,8560	0,8567	0,8766	0,8766	0,8567
Sep-12	0,8577	0,8782	0,9258	0,9258	0,8782
Oct-12	0,8896	0,8908	0,8986	0,8986	0,8908
Nov-12	0,9175	0,9436	0,9466	0,9466	0,9436
Dec-12	0,9392	0,9971	1,0000	1,0000	0,9971
Jan-13	0,8940	0,8942	0,9501	0,9501	0,8942
Feb-13	0,8883	0,8899	0,9516	0,9516	0,8899
Mar-13	0,8300	0,8781	1,0000	0,8781	1,0000
Apr-13	0,9109	0,9656	1,0000	0,9656	1,0000
May-13	0,8911	0,9180	0,9741	0,9741	0,9180
Jun-13	0,9147	0,9299	1,0000	1,0000	0,9299
Jul-13	0,8906	0,9575	1,0000	1,0000	0,9575
Aug-13	0,9011	1,0000	1,0000	1,0000	1,0000
Sep-13	0,8765	0,8878	0,9022	0,9022	0,8878

	Actual normalised	Constant RTS	Variable RTS	Non-increasing RTS	Non-decreasing RTS
Oct-13	0,9158	0,9449	0,9452	0,9452	0,9449
Nov-13	0,9246	0,9361	0,9447	0,9361	0,9447
Dec-13	0,8836	0,8896	0,9185	0,9185	0,8896

Appendix B.2 : Energy efficiency tracking results

Table B-4*: Monthly energy efficiencies of Plant A, Plant B and Plant C.*

	Plant A efficiency	Plant B efficiency	Plant C efficiency
Jan-12	29,5041%	32,5361%	32,8457%
Feb-12	27,7412%	28,7636%	33,1668%
Mar-12	27,4421%	31,5944%	36,8758%
Apr-12	29,3480%	31,7522%	35,5568%
May-12	29,9837%	31,6061%	33,3142%
Jun-12	30,5145%	31,6583%	33,1908%
Jul-12	30,6626%	31,6885%	36,7776%
Aug-12	31,4540%	31,7956%	31,5652%
Sep-12	31,0338%	31,8551%	31,6268%
Oct-12	31,2109%	32,1019%	32,8030%
Nov-12	31,0619%	32,1229%	33,8323%
Dec-12	31,3671%	31,9371%	34,6353%
Jan-13	29,9213%	31,8549%	32,9660%
Feb-13	29,1946%	31,4353%	32,7579%
Mar-13	29,2076%	31,8579%	30,6053%
Apr-13	29,3573%	31,4755%	33,5917%
May-13	27,3362%	31,0668%	32,8602%
Jun-13	27,2255%	30,6243%	33,7291%
Jul-13	27,7572%	30,9796%	32,8424%
Aug-13	27,1241%	31,0114%	33,2304%
Sep-13	25,8916%	30,9704%	32,3205%
Oct-13	28,9342%	30,9993%	33,7707%
Nov-13	29,9301%	30,0411%	34,0942%
Dec-13	28,6264%	29,9234%	32,5850%
Average	**29,0447%**	**31,3136%**	**33,3019%**

Table B-5*: Scaled monthly DEA energy efficiency plant comparison results.*

	Plant A	Plant B	Plant C
Jan-12	0,9430	1,0000	0,8914
Feb-12	0,8864	0,8914	0,9044
Mar-12	0,8813	0,9746	1,0000
Apr-12	0,9366	0,9836	0,9808
May-12	0,9603	0,9718	0,9103
Jun-12	0,9733	0,9781	0,9583
Jul-12	0,9775	0,9801	1,0000
Aug-12	1,0000	0,9890	0,8567
Sep-12	0,9921	0,9808	0,8782
Oct-12	1,0000	0,9884	0,8908
Nov-12	1,0000	0,9941	0,9436

	Plant A	Plant B	Plant C
Dec-12	1,0000	1,0000	0,9971
Jan-13	0,9590	0,9799	0,8942
Feb-13	0,9252	0,9665	0,8899
Mar-13	0,9346	0,9798	0,8781
Apr-13	0,8725	0,9722	0,9656
May-13	0,8710	0,9561	0,9180
Jun-13	0,8565	0,9426	0,9299
Jul-13	0,8866	0,9536	0,9575
Aug-13	0,8537	0,9636	1,0000
Sep-13	0,8138	0,9537	0,8878
Oct-13	0,8664	0,9545	0,9449
Nov-13	0,9431	0,9241	0,9361
Dec-13	0,8591	0,9269	0,8896

Appendix B.3 : DEA mass and calorific content analysis results

Table B-6: *Monthly DEA mass and calorific value results for Plant A, Plant B and Plant C.*

	Plant A	Plant B	Plant C
Jan-12	0,9627	0,9773	0,9587
Feb-12	0,9286	1,0000	0,9284
Mar-12	0,9073	0,9846	1,0000
Apr-12	0,9950	1,0000	1,0000
May-12	0,9878	0,9833	1,0000
Jun-12	1,0000	0,9869	0,9565
Jul-12	0,9948	0,9891	1,0000
Aug-12	1,0000	1,0000	0,8749
Sep-12	0,9888	1,0000	0,9215
Oct-12	0,9995	1,0000	0,9187
Nov-12	1,0000	1,0000	0,9495
Dec-12	1,0000	1,0000	1,0000
Jan-13	1,0000	0,9933	0,9502
Feb-13	1,0000	0,9822	1,0000
Mar-13	0,9763	0,9948	1,0000
Apr-13	0,9699	0,9854	1,0000
May-13	1,0000	0,9754	0,9703
Jun-13	1,0000	0,9596	1,0000
Jul-13	1,0000	0,9707	1,0000
Aug-13	1,0000	0,9723	1,0000
Sep-13	0,9245	0,9656	0,9450
Oct-13	1,0000	1,0000	1,0000
Nov-13	1,0000	0,9401	1,0000
Dec-13	0,9362	0,9334	0,9306

Appendix B.4 : DEA efficiency tracking with climate factors

Table B-7: *Average monthly maximum temperature and total monthly rainfall for case study plants.*

	Plant A temperature (degrees Celsius)	Plant A rainfall (mm)	Plant B temperature (degrees Celsius)	Plant B rainfall (mm)	Plant C temperature (degrees Celsius)	Plant C rainfall (mm)
Jan-12	28,3000	93,0000	17,0000	122,1740	2,2222	21,8440
Feb-12	29,8000	24,5000	16,2222	81,5340	3,7778	40,8940
Mar-12	28,4000	70,5000	24,6111	166,8780	13,5000	75,9460
Apr-12	25,0000	31,0000	26,1111	104,3940	11,5000	74,6760
May-12	25,5000	0,0000	30,7222	110,2360	19,8889	66,0400
Jun-12	18,5000	3,0000	33,7222	86,8680	26,1111	34,0360
Jul-12	20,9000	0,0000	34,8889	102,8700	30,2778	135,8900
Aug-12	23,2000	2,0000	35,0000	73,9140	26,7222	67,0560
Sep-12	23,2000	130,0000	32,2778	55,1180	23,0000	68,8340
Oct-12	26,5000	60,0000	24,5000	53,5940	15,2778	90,1700
Nov-12	27,2000	108,0000	21,3889	74,4220	8,5000	10,9220
Dec-12	27,3000	78,0000	16,7778	117,6020	5,1111	101,8540
Jan-13	28,5000	131,0000	14,2778	69,8500	0,5000	94,9960
Feb-13	30,5000	57,0000	16,0000	72,8980	0,2000	66,8020
Mar-13	28,5000	67,0000	18,7778	19,3040	2,5000	37,5920
Apr-13	23,8000	107,0000	26,1111	94,9960	10,6111	205,2320
May-13	22,2000	7,0000	30,1111	97,5360	18,1111	114,3000
Jun-13	21,0000	0,0000	35,0000	102,3620	22,3889	141,4780
Jul-13	20,6000	0,0000	35,5000	14,7320	26,0000	46,4820
Aug-13	21,0000	0,0000	38,3889	15,4940	26,1111	99,0600
Sep-13	27,0000	13,0000	35,8889	251,2060	23,0000	45,9740
Oct-13	27,4000	185,0000	30,6111	156,7180	15,2778	69,5960
Nov-13	28,6000	182,0000	30,6111	100,3300	6,7778	86,1060
Dec-13	25,6000	236,5000	30,6111	106,6800	0,1000	41,4020

***Table B-8**: DEA EE and average monthly coal moisture content for 2012.*

	Plant A DEA EE	Plant A average monthly coal moisture
Jan-12	0,9430	8,9876
Feb-12	0,8864	8,6425
Mar-12	0,8813	8,5703
Apr-12	0,9366	8,0473
May-12	0,9603	7,9199
Jun-12	0,9733	7,6447
Jul-12	0,9775	8,1608
Aug-12	1,0000	7,3620
Sep-12	0,9921	8,0154
Oct-12	1,0000	8,7164
Nov-12	1,0000	7,7703
Dec-12	1,0000	8,0920

***Table B-9**: DEA including coal moisture content for Plant A.*

	With coal moisture content data	Without coal moisture content data

	With coal moisture content data	Without coal moisture content data
Jan-12	0,959753715	0,953634382
Feb-12	0,913743408	0,908162991
Mar-12	0,903069735	0,898224655
Apr-12	0,968884903	0,964092733
May-12	0,97998475	0,968696336
Jun-12	0,997015738	0,992000927
Jul-12	0,993442024	0,990215029
Aug-12	1	1
Sep-12	0,990191659	0,982222573
Oct-12	0,998241984	0,997470835
Nov-12	1	1
Dec-12	1	1

Appendix B.5 : DEA efficiency with capacity factor

Table B-10: *Monthly capacity factor for case study plants.*

	Plant A (%)	Plant B (%)	Plant C (%)
Jan-12	0,6032	0,8115	0,3005
Feb-12	0,5471	0,7799	0,7474
Mar-12	0,4788	0,6940	0,3744
Apr-12	0,5276	0,5272	0,3624
May-12	0,6698	0,5834	0,2409
Jun-12	0,6599	0,6835	0,4403
Jul-12	0,6099	0,8114	0,3747
Aug-12	0,6520	0,8314	0,4188
Sep-12	0,5753	0,4278	0,5858
Oct-12	0,5220	0,5806	0,3927
Nov-12	0,4618	0,8310	0,4508
Dec-12	0,3370	0,8222	0,5341
Jan-13	0,3313	0,6693	0,5130
Feb-13	0,3971	0,5941	0,5916
Mar-13	0,5172	0,5526	0,2792
Apr-13	0,5483	0,5749	0,3620
May-13	0,6131	0,5323	0,6048
Jun-13	0,7713	0,6080	0,6268
Jul-13	0,7468	0,6769	0,6932
Aug-13	0,6524	0,6824	0,4400
Sep-13	0,7124	0,6354	0,4470
Oct-13	0,7490	0,3839	0,3995
Nov-13	0,7865	0,5771	0,3766
Dec-13	0,6021	0,6756	0,4354

Table B-11: *DEA including monthly average capacity factor for Plant A.*

Jan-12	0,9154
Feb-12	0,9321
Mar-12	0,8628

Apr-12	0,9567
May-12	0,9304
Jun-12	0,9819
Jul-12	0,9476
Aug-12	0,9939
Sep-12	0,9741
Oct-12	0,9540
Nov-12	0,9851
Dec-12	0,9601
Jan-13	0,9471
Feb-13	1,0000
Mar-13	0,8982
Apr-13	0,9243
May-13	0,8807
Jun-13	0,9035
Jul-13	1,0000
Aug-13	0,8669
Sep-13	0,8483
Oct-13	0,9111
Nov-13	0,9284
Dec-13	0,8593

Appendix B.6 : DEA efficiency tracking of plant environmental impact

***Table B-12**: DEA Eco-efficiency results for Plant A.*

	Eco-efficiency DEA	**EE DEA**
Jan-12	97,05%	94,30%
Feb-12	88,20%	88,64%
Mar-12	87,25%	88,13%
Apr-12	93,30%	93,66%
May-12	95,88%	96,03%
Jun-12	100,00%	97,33%
Jul-12	99,62%	97,75%
Aug-12	100,00%	100,00%
Sep-12	98,66%	99,21%
Oct-12	99,23%	100,00%
Nov-12	98,75%	100,00%
Dec-12	99,72%	100,00%

Appendix C: DEA energy efficiency with monthly averaging results

Appendix C.1 : Monthly averaging results

***Table C-1**: Monthly average EE and DEA results for Plant A.*

	EE (normalised)	**DEA EE**
Jan-12	0,9175	0,9197
Feb-12	0,9054	0,9091

Mar-12	0,9015	0,9049
Apr-12	0,9286	0,9322
May-12	0,9597	0,9606
Jun-12	0,9721	0,9713
Jul-12	0,9883	1,0000
Aug-12	0,9940	1,0000
Sep-12	1,0000	1,0000
Oct-12	0,9955	0,9972
Nov-12	0,9986	1,0000
Dec-12	0,9867	1,0000
Jan-13	0,9625	0,9666
Feb-13	0,9390	0,9486
Mar-13	0,9265	0,9463
Apr-13	0,9055	0,9152
May-13	0,8799	0,8835
Jun-13	0,8739	0,8796
Jul-13	0,8690	0,8912
Aug-13	0,8535	0,8591
Sep-13	0,8609	0,8656
Oct-13	0,8868	0,8438
Nov-13	0,9146	0,8511
Dec-13	0,8820	0,7513

Table C-2: *Moving average EE and DEA results for Plant B.*

	EE	DEA EE
Jan-12	0,9557	0,9564
Feb-12	0,9648	0,9654
Mar-12	0,9516	0,9564
Apr-12	0,9872	0,9873
May-12	0,9880	0,9881
Jun-12	0,9876	0,9877
Jul-12	0,9895	1,0000
Aug-12	0,9910	0,9912
Sep-12	0,9954	0,9954
Oct-12	1,0000	1,0000
Nov-12	0,9998	1,0000
Dec-12	0,9976	1,0000
Jan-13	0,9913	0,9915
Feb-13	0,9898	0,9898
Mar-13	0,9855	0,9856
Apr-13	0,9817	0,9818
May-13	0,9685	0,9685
Jun-13	0,9636	0,9637
Jul-13	0,9634	0,9636
Aug-13	0,9667	0,9682
Sep-13	0,9669	0,9670
Oct-13	0,9558	0,9558
Nov-13	0,9426	0,9426

Dec-13	0,9352	0,9353

Table C-3: *Results of DEA with fuel mass and coal moisture content for Plant A with monthly averaging.*

Jan-12	0,9422
Feb-12	0,9311
Mar-12	0,9313
Apr-12	0,9554
May-12	0,9852
Jun-12	0,9931
Jul-12	1,0000
Aug-12	1,0000
Sep-12	0,9985
Oct-12	1,0000
Nov-12	1,0000
Dec-12	1,0000

Table C-4: *Results of DEA with fuel mass and calorific content with monthly averaging.*

Jan-12	0,9370
Feb-12	0,9265
Mar-12	0,9277
Apr-12	0,9506
May-12	0,9794
Jun-12	0,9863
Jul-12	1,0000
Aug-12	0,9923
Sep-12	0,9944
Oct-12	0,9942
Nov-12	1,0000
Dec-12	1,0000
Jan-13	1,0000
Feb-13	0,9818
Mar-13	0,9567
Apr-13	0,9334
May-13	0,9222
Jun-13	0,9871
Jul-13	1,0000
Aug-13	0,9565
Sep-13	0,9069
Oct-13	0,9181
Nov-13	0,9333
Dec-13	0,8900

Table C-5 *: DEA eco-efficiency results for Plant A with monthly averaging.*

Jan-12	92,21%

Feb-12	90,68%
Mar-12	90,15%
Apr-12	92,86%
May-12	96,50%
Jun-12	99,19%
Jul-12	100,00%
Aug-12	100,00%
Sep-12	100,00%
Oct-12	99,55%
Nov-12	99,86%
Dec-12	98,67%

Appendix D : DEA energy efficiency with averaging over multiple calendar years results

Appendix D.1 : Two year yearly average DEA results

***Table D-1**: EE DEA results for case study plants with two year yearly average data.*

	Plant A	Plant B	Plant C
January	1,0000	1,0000	0,9563
February	0,9647	0,9370	0,9586
March	0,9485	0,9890	0,9826
April	0,9741	0,9976	1,0000
May	0,9644	0,9732	0,9580
June	0,9697	0,9672	0,9700
July	1,0000	0,9866	1,0000
August	1,0000	1,0000	0,9453
September	0,9327	0,9722	0,9250
October	0,9957	0,9836	0,9648
November	1,0000	0,9753	0,9837
December	0,9759	1,0000	0,9788

***Table D-2**: Fuel mass and calorific value DEA results for case study plants with two year yearly average data.*

	Plant A
January	0,8763
February	1,0000
March	0,7848
April	0,8360
May	0,9106
June	1,0000
July	1,0000
August	1,0000
September	0,7277
October	0,7153
November	0,7068
December	0,6289